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Models of Credit Risk for Emerging Markets

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Industrial and Financial Economics
Master Thesis No 2005:1
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ABSTRACT

The problem of accurate credit risk evaluation is well-known in the world of financial markets. This paper develops a series of credit risk models using multiple discriminant analysis (the MDA) for selected emerging markets within which Financial company A (FcA) provides credit. This paper investigates the discriminating power of various explanatory variables to distinguish between good and bad credit risks within each selected market in order to develop new market-specific credit scoring models for FcA. A comparative analysis of the classification accuracy of these new models and the existing model used by FcA is conducted. This analysis shows that the new models are robust and classify credit risks significantly more accurately than the existing model.

Keywords: **Credit Risk, Emerging Markets, Credit Scoring Model, Multiple Discriminant Analysis, Z-Score Model**

ACKNOWLEDGEMENTS

I would like to take this opportunity to thank people that have helped me with this work. Without their knowledge and encouragement, the finishing point of this study would have been harder to achieve successfully.

I would like to express my thankfulness to Charles Nadeau for his recommendations and support with this thesis and for being my supervisor.

I would also like to thank managers and other employees of Financial company A for their countenance, useful feedbacks and helpful advices that I received doing this work.

Pavel Gusev

Goteborg, December 2005

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1. INTRODUCTION

Lenders started to analyze the risks involved since the 19th century. Mainly, they were focused on the analysis of accounting ratios. At that time, there were no other techniques to detect company's operating and financial difficulties apart from the analysis of accounting ratios. This kind of analysis was univariate – every accounting ratio was considered individually. In order to satisfy lender's demand for information, rating agencies were established to supply a qualitative type of information assessing the credibility of particular traders. For instance, the predecessor of the well-known Dun & Bradstreet, Inc. was established in 1849 in Ohio, with the purpose of providing independent credit investigations.

The next period of default prediction research works began from the middle of the 20th century by new default prediction methods pioneered by Beaver (1967) and Altman (1968). The development of new multivariate techniques for bankruptcy detection was stimulated by the significant growth of computational power of available computers and the appearance of statistical software.

The first credit scoring statistical models were introduced more than 40 years ago, but their implementation is still not easy with respect to the emerging markets, because it's very often the situation that companies from the development countries don't have good book-keeping and other non-quantitative factors are required to be considered. Altman (2002) gives references that about 30-50% of the explanatory power of the scoring model can be provided by qualitative elements, which involve judgment on the part of the risk officer.

The emerging market lending is still subjective process, success of which depends completely on the qualification and experience of credit analysts. The effective credit scoring models for the emerging market, which also help to analyze applications from private small and middle companies, should facilitate the process of decision making in lending and increase decision quality.

2. BACKGROUND

2.1 Problem Definition

This thesis was carried out together with a Swedish firm, Financial company A[1] (FcA). FcA provides services in customer crediting and vehicle leasing from the year 1998. During the last years, FcA increases its activity on the emerging markets of Eastern Europe and Asia. The credit portfolio of FcA consists of the commercial vehicles sold on credit.

The overwhelming majority of credits, provided to the end-customers, is denominated in the EURO. During the credit period customers are repaying a financing provided by FcA. FcA is interested to predict beforehand future payment performance of its customers, in order to avoid loss.FcA has plans to build a new credit scoring model, which reflects the experience of their credit analysts on the emerging markets.

In the scope of this work, the following questions will be investigated:

(1) which explanatory variables play the most important role (maximizing the variance) in the discrimination between "bad" and "good" borrowers (it could be economic and political variables) for the selected emerging markets,
(2) how we can explain our findings – the sets of discriminating variables for each particular market,
(3) how accurately the new model is able to classify new credit applications between "bad" and "good" credit borrowers in comparison with the existing credit scoring model, which is currently used by FcA.

2.2. Purpose

The points of this work were discussed with FcA mangers. On the basis of their requirements, purposes of this work were determined.

The purposes of this thesis are:

[1] Due to confidentiality, concerning the new credit scoring model, the firm cannot be mentioned by real name.

(1) to build the new credit scoring model on the base of multiple discriminant analysis (the MDA) in order to improve a quality of decision making in the field of business loan evaluation,
(2) to check the discrimination power of the potential variables for the new credit scoring model,
(3) to adopt the credit score model on the base of the MDA to the emerging markets where FcA is performing its business activity,
(4) to predict the classification of a new credit application on the base of derived discriminating variables,
(5) to provide a comparison of classification accuracy between new and old credit scoring models on the base of credit stories of FcA clients.

2.3. Literature Review

Altman, E. & Saunders, A. (1998) emphasize the forces, which have the greatest impact on the credit risk measurement evolution during the last 20 years: (i) a worldwide structural increase in the number of bankruptcies, (ii) a trend towards disintermediation by the highest quality and largest borrowers, (iii) more competitive margins on loans, (iv) a declining value of real assets (and thus collateral) in many markets, (v) a dramatic growth of off-balance sheet instruments with inherent default risk exposure, including credit risk derivatives.

Altman, E. & Saunders, A. divide the approaches undertaken by practitioners to solve the credit risk problem by the following categories:

(1) developing new and more sophisticated credit scoring/early-warning systems,
(2) developing measures of credit concentration risk (the measurement of portfolio risk) ,
(3) developing new models to price credit risk ,
(4) developing models to measure better the credit risk of off-balance sheet instruments .

As you can see all the measures, aimed to solve the problem of the credit risk, assume an implementation of the statistical credit scoring models.

Mester (1997) defines credit scoring as a method of evaluating the credit risk of loan applications. Credit scoring produces a “score” that a lender can use to rank its borrowers or loans in terms of risk. Credit scoring helps to segregate the impact of various applicant characteristics on frauds and defaults. Merter describes the process of a scoring model building as an analysis of historical data on the performance of previously made loans in order to determine which borrower characteristics are useful in predicting whether the loan performed well.

Altman, E. & Saunders, A. conclude that almost all of today’s models estimating the probability of default (PD) are variations of a similar approach, which involves the combination of a set of quantifiable financial indicators with additional qualitative variables. Today’s traditional models estimating PD can be also classified. Allen (2002) gives us the next three main categories of the traditional models to predict default:

(1) Expert systems and artificial neural networks,
(2) Rating systems,
(3) Credit scoring models.

Expert systems are systems based on the human judgment of commercial loans. Such systems were very popular historically among bankers for the assessing of credit quality. Expert systems are based on the reputation, the leverage, the earning volatility, the macroeconomic conditions. Unfortunately, human experts may be inconsistent or subjective in their assessments. That is why neural networks have been invented to evaluate experts judgments more impartially and constantly. Indisputable advantage of neural networks is ability to incorporate changing conditions into the decision making process using historical repayment experience and default data.

Rating systems are based on extensive human analysis of both quantitative and qualitative performance of a firm. For example, well-known agencies using rating systems for companies' external debt estimation are Standard & Poor's and Moody's. But rating systems from external agencies tend to be used for the credibility evaluation of large and publicly traded companies (Moody's, 2000).Many banks have their own internal ranking systems. Usually, the architecture of the internal rating system can be one-dimensional, in which an overall rating is assigned to each loan based on the probability of default (PD), or two-dimensional, in which each borrower's PD is assessed separately from the loss severity of the individual loan (Allen, 2002).

Mester classifies today's credit scoring models by 4 main groups according to used statistical methods:

(1) the linear probability model,

(2) the logit model,

(3) the probit model,

(4) the multiple discriminant analysis models.

These models categorize financial variables that have significant statistical explanatory power in differentiating between defaulting and non-defaulting borrowers. Each applicant is given a Z-score assessing their categorization as "good" or "bad" on the base of variable included in the particular multivariate credit scoring models. The Z-score itself also can be presented as a probability of default.

First credit scoring systems based on the multiple discriminant credit scoring analysis were introduced by Altman (1968). Altman used a multivariate approach analyzing ratio-level and categorical (qualitative) univariate variables. Using the combination of those weighted variables, he got a credit risk score that best discriminates between default and non-default companies. The Z-Score model was created using the MDA technique. Altman implemented the next actions to create the Z-score model: (i)observation of the statistical significance of various alternative functions, including determination of the relative contributions of each independent variable; (ii) evaluation of correlations among the relevant variables; (iii) observation of the predictive accuracy of the various profiles; and (iv) judgment of the analyst. Finally, he selected five[2] variables to construct the following discriminant function (Altman, 1968):

$$\mathbf{Z = 0.012(X_1) + 0.014(X_2) + 0.033(X_3) + 0.006(X_4) + 0.999(X_5),} \qquad \mathbf{[2.1]}$$

where X_1 = working capital/total assets,
X_2 = retained earnings/total assets,
X_3 = earnings before interest and taxes/total assets,
X_4 = market value of equity /total liabilities,
X_5 = sales/total assets, and Z = overall index ($Z < 1.81$ indicates a distressed condition).

Unfortunately, private companies can't use the Z-score model, because the ratio X_4 assumes that company is publicly traded. Altman (1993) provides revision of the Z-Score model for private manufacturing companies substituting the book values of equity for the market value in X4[3]:

$$\mathbf{Z' = 0.717(X1) + 0.847(X2) + 3.107(X3) + 0.420(X4) + 0.998(X5),} \quad \mathbf{[2.2]}$$

where X_1 = working capital/total assets,
X_2 = retained earnings/total assets,
X_3 = earnings before interest and taxes/total assets,
X_4 = book value of equity /total liabilities,
X_5 = sales/total assets, and Z' = overall index ($Z < 1.23$ indicates a distressed condition).

The next modification of the Z-Score model for private non-manufacturing companies is without X5 - sales/total assets. Assets turnover is an industry-

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[2] The original set for Altman's analysis contained 22 variables

[3] The reason for this substitution is that original the Z-Score model is a publicly traded firm model. To assume *ad hoc* adjustments of the Z-score for private companies is scientifically invalid.

sensitive variable, which varies significantly by industry. This modification of the Z-Score model is:

$$\mathbf{Z'' = 6.56(X1) + 3.26(X2) + 6.72(X3) + 1.05(X4),} \qquad \textbf{[2.3]}$$

where X_1 = working capital/total assets,
X_2 = retained earnings/total assets,
X_3 = earnings before interest and taxes/total assets,
X_4 = book value of equity /total liabilities, Z'' = overall index (Z < 1.10 indicates a distressed condition).

Also Altman, Hartzell and Peck (1995) implied enhanced Z'' formula[4] for the emerging markets companies, Mexican firms issued Eurobonds denominated in US dollars.

According to Altman and Narayanan (1997), international versions of Z-score models have been developed in over 25 countries. It is noticeable, that according to the conducted studies, there are not so many the models' differences across countries of different sizes and in various stages of development, but rather their similarities. Most provided studies found that financial ratios measuring profitability, leverage, and liquidity had the most statistical power in differentiating defaulted from non-defaulted firms. Deficiencies of existing credit scoring models are data limitations and the assumption of linearity.

Mester provides facts of the extensive use of credit scoring models: 97 percent of banks in the US use credit scoring to approve credit card applications, whereas 70 percent of the banks use credit scoring in their small business lending.

Credit scoring models are the most widespread category of default-prediction methods in today's financial world, because of its comparatively low costs and

[4] Z'' formula was modified as: Z'' = 6.56(X1) + 3.26(X2) + 6.72(X3) + 1.05(X4) + 3.25, where the constant (3.25) for the standardization with a default rating (D), which is used for bond rating.

ease of implementation. Also we can note that these models are able to avoid the bias and contradiction of expert systems.

As an addition to the traditional models for the default prediction, we have two modern alternative approaches: an options-theoretic structural approach pioneered by Merton (1974) and a reduced form approach utilizing intensity-based models to estimate stochastic hazard rates established by works of Jarrow and Turnbull (1995), Jarrow, Lando, and Turnbull (1997), and Duffie and Singleton (1998, 1999), (Allan, 2002). For example, Moody's KMV (EDF[5]) formula is built on the Merton's approach. We will not consider modern methods of default prediction as alternatives for the credit scoring models on the base of the MDA, because they are obtaining borrowers scores from their bond and equity prices. In this thesis work we are going to analyze private companies, which have no traded equities.

2.4. Scope and limitations

The building of the new credit scoring model in the scope of this thesis work is based only on the MDA. Other statistical methods, which are also used in the credit scoring systems, will not be considered here. Data for the analysis is limited by information provided by FcA. The Romanian sample will be analyzed more thoroughly because of its bigger representativeness.

2.5. Methodology and Data

Methods of investigation:

(1) Statistical information about "bad" and "good" credit borrowers was presented by the Area Managers of FcA. The Area Managers were asked about the possible variables which are not included in the existing model, but are very important according to their professional experience. The criteria of "bad" and "good" samples were developed;

[5] EDF – Expected Default Frequency

(2) The multiple discriminant analysis (the MDA) of the variables from clients' credit applications and the new variables recommended by the Area Managers will be carried out with the help of *STATISTICA* data analysis software. The results of the analysis will determine the discriminating variables maximizing the difference between the "good" and the "bad";

(3) *STATISTICA* software will generate the discriminant classification functions for the classification between "bad" and "good" groups for each new credit application. On the basis of these discrimaint functions the new credit scoring model will be built;

(4) The test of the new model accuracy of classification in comparison with the existing FcA credit scoring model will be applied. Additional set of companies' data, which were not used for the new model building, will be used in order to check the accuracy of the new model[6].

2.6. Outline

Chapter 1 familiarizes readers with the topic of thesis work..
Chapter 2 gives readers the problem definition, the purposes of work, the literature review of credit scoring models development and how the study is outlined.
Chapter 3 exposes theory of the MDA and how it will be used in this thesis.
Chapter 4 describes the process of the new credit scoring model building based on the MDA for the Romanian market.
Chapter 5 provides results of the development of new credit scoring models for other emerging markets.
Chapter 6 gives the results of comparison for the obtained credit scoring models.
Chapter 7 contains summary and conclusions of the paper.

[6] The test of the new credit scoring model accuracy for the independent sample is provided for the Romanian market only

3. MULTIPLE DISCRIMINANT ANALYSIS AS A METHOD FOR BUSINESS CREDIT EVALUATION

3.1 Multiple discriminant analysis

According to Altman's work, the multiple discriminant analysis (the MDA) is a procedure used to classify an object into one of several *a priori* groupings dependant upon the individual characteristics of the object[7]. Even though not as popular as regression analysis, the MDA statistical technique had been used in a variety of disciplines since its first application in 1930's. Before the end of 1960's, the MDA was used mainly in biology and sociology. the MDA became very popular technique in the practical business world since the beginning of 1970's.

The fundamental idea underlying the MDA is to verify whether groups differ regarding to the mean of a variable, and than to use that variable for the prediction of group membership. If a particular object, for instance, a firm, has variables (financial ratios) that can be quantified for all of the companies in the analysis, the MDA determines a set of discriminant coefficients. We can classify a company into "good" or "bad" group applying these coefficients. When these coefficients are applied to the actual ratios, a basis for classification into one of the mutually exclusive groups exists. The main plus of the MDA technique is ability to consider an entire set of characteristics common to the relevant firms, as well as the interaction of these properties. In contrast, a univariate study, for instance the traditional ratio analyses, can only consider the variables used for group assignments just one by one.

From the computational practical approach, the MDA is very similar to analysis of variance (ANOVA).

[7] Altman (1988)

3.1.1 Analysis of variance

The MDA analysis problem can be considered as an analysis of variance (ANOVA) problem. The main goal of the analysis of variance to determine, whether or not two groups are significantly different from each other regarding to the mean of selected variable. If the means of variables are significantly different in different groups, then that selected variable discriminates between the groups.

In the simple case of just one variable, F test is used as the final significance test of discrimination between groups. F is calculated as the ratio of the between-group variance in the data over the average within-group variance. If the between-group variance is significantly larger then within-group, then it must be significant differences between means.

3.1.2 Multiple Variables

In the case of our credit scoring model, we have more than one variable, because the goal of this research is to find out which variables are playing the most important role for the discrimination between "good" and "bad" customers.

Having multiple variables we have a matrix of total variances and covariances between groups and a matrix of pooled within-group variances and covariances. Multivariate F-tests are used to find any significance difference between groups with regard to all variables throughout the comparison of those matrixes.

This operation is similar to multivariate analysis of variance (MANOVA).We need to launch the multivariate F-test and, if statistically significant, continue to see which variables have significantly dissimilar means across the groups.

3.2 Development of the model

The statistical credit scoring model on the base of the MDA was built in order to improve a quality of decision making about customer credits. The main purpose of the model is to be able to predict to which group of customers a new applicant belongs on the base of selected variables. In the further discussion we will use the terms “in the model” (“not in the model”) for variables, which are included (excluded) in the prediction of the group membership.

3.2.1 Forward stepwise analysis

In order to perform the forward stepwise discriminant function analysis, *STATISTICA* data analysis software was chosen to create a model of discrimination between groups step-by-step. At each step of the MDA procedure, *STATISTICA* reviews all variables and estimate, which one will add most to the discrimination between groups. This variable will then be added in the model, and *STATISTICA* goes to the next step of analysis.

3.2.2 Backward stepwise analysis

Also *STATISTICA* provides opportunity to make the MDA in the backward direction. In that case *STATISTICA* first includes all variables in the model and then, at each step, eliminates the variable that contributes least to the prediction of group membership. Finally, just the most significant variables for the between-group discrimination remain in the model.

3.2.3 F to enter, F to remove

When *STATISTICA* performs the forward stepwise analysis or the backward stepwise analysis, it uses F to enter or F to remove values respectively. The F value for a variable indicates the presence or absence of statistical significance in the discrimination between groups. The F value measures the extent to which a variable makes a unique contribution to the prediction of group membership. We can interpret the F to enter/remove values in the same way as in the stepwise multiple regression procedure.

STATISTICA continues the process of selection of variables to be included (excluded) in the model, as long as the respective *F* values for those variables are larger (less) than the user-specified *F* to enter (to remove).

3.2.4 Multiple Discriminant Analysis for a Two-group case

In this paper, we are building the credit scoring model considering just two possible groups of customers as "good" and "bad". The MDA for a two-group case is similar to the multiple regression. This analysis is also known as Fisher linear discriminant analysis[8].

If we code the two groups in the analysis as *"good"* and *"bad"*, and use that variable as the dependent variable in a multiple regression analysis, then we would get results that are analogous to those we would obtain via the MDA. But Altman (1988) emphasizes one important difference between the MDA and the multiple regression analysis. The MDA is able to make forecasts or predictions in problems where the dependant variable appears in dichotomous form, i.e., true or false, yes or no. In contrast, the multiple regression analysis requires a quantification of the dependant variable.

In our two-group case we fit a linear equation (canonical discriminant function) of the following form:

$$\mathbf{f_{km} = u_0 + u_1{*}X_{1km} + u_2{*}X_{2km} + \ldots + u_p{*}X_{pkm}\,, \qquad [3.1]}$$

where f_{km} is the value(score) on the canonical discriminant function for case m in the group k,
X_{ikm} is the value on discriminating variable X_i for case m in group k,
ui are regression coefficients which produce the desired characteristics in the function.

[8] Fisher linear discriminant analysis was introduced by Fisher R. in 1936 in his work "The Utilization of multiple Measurements in Taxonomic Problems". Annals of Eugenics. 7, p.179-188.

We derive regression coefficients for the first canonical function in order to get the group means on the function as different as possible. The coefficients for all next functions are also derived to maximize the difference between the group means, but taking into account that values on the each next function are not correlated with the previous ones. The maximum number of unique functions in this case is equal to the number of group minus one or the number of discriminating variables between groups, if this number is fewer. In the case of our research, we have just two groups and 12 discriminating variables. Therefore, we can derive just one canonical discriminant function.

Other important interpretation of the results of the MDA for a two-group case problem is clear-cut and closely follows the logic of multiple regression. Variables with the largest regression (standardized) coefficients contribute the most to the prediction of group membership.

3.2.5 Deriving the canonical discriminant function coefficients

For the deriving of the canonical discriminant function coefficients is possible to use the T matrix of total sums of squares and cross-products T is a square symmetric matrix[9].Elements of T matrix are presented by the following equation:

$$\mathbf{t_{ij}=\sum_{k=1}^{g}\sum_{m=1}^{n_k}(X_{ikm}-X_i)(X_{jkm}-X_j)}\ , \quad \mathbf{[3.2]}$$

where g is the number of groups,
n_k is the number of cases in group k,
n is the total number of cases over all groups,
X_{ikm} is the value of variable i for case m in group k,
X_i is the mean value of variable i for all cases (total mean).

[9] A matrix is square symmetric when the number of rows is equal to the number of columns and the upper-right triangle is a reflection of the lower-left triangle (t_{ij}=tji). Klecka (1980), p. 66.

We can interpret the terms in parenthesis as the amount by which the value of variable i in the particular case m deviates from the total mean X_i on that variable i.

In order to check the significance of relation between two variables, we can use the correlation matrix of variables. The total correlation coefficients matrix would be obtained by dividing of each element of T matrix by the square root of the product of the two diagonal elements in the same row and column.

If the group locations are not identical, then the degree of within group dispersion is less than the total dispersion. The matrix W is calculated to measure how the degree of within group dispersion is less than the total dispersion. W is also called the within-group sums of squares and crossproducts matrix. Elements of W are derived in the next way:

$$\mathbf{w_{ij}=\sum_{k=1}^{g}\sum_{m=1}^{n_k}(X_{ikm}-X_{ik})(X_{jkm}-X_{jk}),\quad [3.3]}$$

where X_{ik} is the mean value of variable i for those cases in group k.

We can easily convert W matrix into a within-groups correleation matrix using the same algorithm as for the convertation of T matrix into the total correlation matrix.

All elements of W are the same as elements of T ,if there are no difference among the groups centroids[10] ($X_{ik}=X_i$). If centroids are different , the elements of W are smaller than the corresponding elements of T. This difference is measured by matrix B. The elements of B are calculated as:

$$\mathbf{B=T-W\ (i.e,\ b_{ij}=t_{ij}-w_{ij}),\qquad [3.4]}$$

[10] Centroid's definition is introduced in the chapter 3.3.4

B has the name of the between-groups sums of squares and crossproducts matrix.The size of corresponding elements of B and W shows the difference between groups.

W and B have all required basic information about the relationship within the group and between them. We can obtain a formula describing these properties by solving the next system of equations:

$$\sum \mathbf{b_{1i}v_i} = \lambda \sum \mathbf{w_{1i}v_i}$$
$$\sum \mathbf{b_{2i}v_i} = \lambda \sum \mathbf{w_{2i}v_i}$$
.
.
.
$$\sum \mathbf{b_{pi}v_i} = \lambda \sum \mathbf{w_{pi}v_{i,}} \qquad \textbf{[3.5]}$$

where λ is a constant called the "eigenvalue"[11],
v's are a set of p coefficients,
b's the between-groups sums of squares and crossproducts,
w's the within-groups sums of squares and crossproducts.

In order to solve this system of equations, we are assuming that the sum of the squared values of the v's is equal to 1.0.There are a maximum of q unique, non-trivial solutions for this system. Each solution of the system, which has its own λ and set of v's, refers to one canonical discriminant function.
It's possible to use the v's coefficients for the discriminant functions. But we can use the u's coefficients from the Equation [3.1], which give the discriminant function better properties. The u's coefficients could be defined throughout the v's coefficients:

$$\mathbf{u_i} = \mathbf{v_i}\sqrt{n-g} \ \ \textbf{and}\ \mathbf{u_0} = -\sum_{i=1}^{p} u_i X_i\,, \qquad \textbf{[3.6]}$$

[11] More detailed interpretation of "eigenvalue" is provided in the chapter 4.3.4

Using the u's coefficients , we can calculate the discriminant scores f's for the data cases in the standard form. It means that that the discriminant scores f's over all the cases will have a mean of zero and within-groups standard deviation one. Klecka (1980) also emphasizes that the discriminant score for a given case represents the position of that case along the continuum (axis) defined by the discriminant canonical function.

3.2.6 Assumptions

The MDA is very similar to the multiple regression analysis. And all assumptions, which are valid for the multiple regression analysis, are also valid for the MDA. We need be aware of these possible pitfalls when we are using results of the MDA:

(1) It is assumed that variance/ covariance matrices of variables are homogenous across groups. However, it is required to notice that Lachenbruch (1975) indicates that the MDA is relatively robust even when there are modest violations of this assumption. Klecka (1980) points out those dichotomous variables, which often violate multivariate normality, are not likely to affect conclusions based on the MDA;

(2) When the means for variables across groups are correlated with variances or standard deviations, it could cause considerable threat to the validity of significance test;

(3) It is assumed that the selected sample of data is normally distributed;

(4) Another important assumption is that the variables for the analysis are not completely redundant. If any one of the variables is completely redundant with the other variables then the matrix is ill-conditioned and can't be inverted in the model.

3.3 Classification of the MDA results

Classification is another important function of the MDA in which the discriminating variables or the canonical discrimination functions are used to predict the group to which a case most likely belongs. After the discriminant functions is derived and the model is finalized, we need be able to estimate how good is our derived model for the group membership prediction.

3.3.1 A priori and post hoc predictions

If we are using one data set to build the best discriminant functions for the between-group classification and then we are using the same data set to estimate the accuracy of classification prediction, we are significantly capitalizing on chance.

Usually, we are getting a worse classification when predicting the cases that were not used for the deriving of the discriminant function.

Post hoc predictions are always better then *a priori* predictions, because it's easier to predict what has happened than what will happen.

It's recommended by different authors never build one's estimations of the classification accuracy of new future cases just on the base of the same data set from which the discriminant functions were obtained. To be sure it's recommended to collect new data for the cross-validation of existing discriminant functions.

3.3.2 Classification functions

These functions differ from the discriminant (canonical) functions introduced in the Chapter 3.2.4. Discriminant functions give us "raw" results which is not convenient to use for the case classification. For this purpose it's better to use special classification functions obtained with the help of *STATISTICA* software.

There are as many classification functions as there are groups. Each classification function allows us to calculate scores for each case, by applying the next equation:

$$\boldsymbol{S_k = c_k + w_{k1}*X_1 + w_{k2}*X_2 + ... + w_{km}*X_m,} \qquad \textbf{[3.7]}$$

where the index *i* denotes the respective group,
the subscripts *1*, *2*, ..., *m* refer to the *m* variables,
c_k is a constant for the *k*'th group,
w_{kj} is the weight (coefficient) for the *j*'th variable in the computation of the classification score for the *k*'th group,
x_j is the observed value for the respective case for the *j*'th variable,
S_k is the resulting classification score for group k.

The weights for the classification function are derived by the following formula:

$$\boldsymbol{w_{ki} = (n\text{-}g)} \sum_{j=1}^{m} a_{ij} X_{jk}\,, \qquad \textbf{[3.8]}$$

where n is the number of groups,
g is the number of cases,
a_{ij} is an element from the inverse of the within-groups sum of crossproducts matrix W,
X_{jk} is the mean value of variable j for those cases in group k,
m is an number of variables entered in the model.
A constant for the k'th group is calculated as :

$$\boldsymbol{c_k = -0.5} \sum_{j=1}^{m} w_{kj} X_{jk}\,, \qquad \textbf{[3.9]}$$

We can use the classification functions for the direct classification scores for new cases.

3.3.3 Classification of cases

The classification of cases becomes easier when we have obtained the classification scores for a case. The case belongs to the group for which it has the highest classification score.

Also it's useful to know the probability that the case belongs to the predicted group. Those probabilities are called posterior probabilities, and can also be computed.

3.3.4 Mahalanobis distances and classification

We can consider that independent variables in the MDA are defining a multidimensional space in which each observation (case) can be plotted. Also, it's possible to plot a point representing the means for all independent variables. This point in the multidimensional space is known as the centroid.

The *Mahalanobis distance*[12] is the distance of a case from the centroid in the multidimensional space, defined by the correlated independent variables. If the independent variables are uncorrelated, this distance is the same as the simple Euclidean distance. Hence, this The *Mahalanobis distance* gives us a signal of whether or not a case is an outlier with respect to the independent variable values.

We can calculate the Mahalanobis distance using the next formula:

$$D^2(X|G_k)=(n-g)\sum_{i=1}^{p}\sum_{j=1}^{p} a_{ij}(X_i-X_{ik})(X_j-X_{jk}), \qquad [3.10]$$

where $D^2(X|G_k)$ is the squared distance from point X (a specific case) to the centroid of group k,
n is the total number of cases over all groups,

[12] The conception of the Mahalanobis distance was developed by an Indian statistician Mahalanobis in 1963

g is the number of groups,
a_{ij} is an element from the inverse of the within-groups sum of crossproducts matrix W,
p is an number of variables entered in the model,
X_{ik} is the mean value of variable i for those cases in group k,
X_i is the mean value of variable i for all cases (total mean).

After the calculation of D^2 for each group, we would classify the case X as belonging to the group k to which it is closest, if the Mahalanobis distance (D^2) is smallest to the centroid of this particular group.

3.3.5 Posterior classification probabilities

We can derive classification probabilities, using the Mahalanobis distances. The probability that a particular case belongs to a particular group is mainly proportional to the Mahalanobis distance from that group centroid. This probability is not exactly proportional because we assume a multivariate normal distribution around each centroid. These probabilities are called posterior probabilities, because they are calculated on the base of our prior knowledge of the values for those case variables in the model.

To summarize, the posterior probability is the probability, based on the knowledge of the values of other variables that the individual case belongs to a particular group. The MDA performed by *STATISTICA* software gives us these probabilities automatically.

3.3.6 A priori classification probabilities

A priori probability is important additional factor, which required to be taken into the consideration when classifying cases. From time to time, we know that some group has more observations than another has. Therefore, *a priori* probability that a case belongs to that group is higher. We can specify different *a priori* probabilities to adjust the classification of cases and also the computation of posterior probabilities. It is always required to consider critically whether the unequal number of cases in different cases is a reflection of the true distribution in the population, or it is just the shortcoming of the sampling procedure. We can set the *a priori* probabilities to be proportional to the sizes of the groups in our sample or ,for instance, as being equal in each group. The accuracy of the prediction can be affected drastically by the specification of different a priori probabilities.

3.3.7 Summary of the prediction

A presentation of the classification results is summarized in the classification matrix. The classification matrix shows the number of cases that were correctly and incorrectly classified by the classification functions.

3.3.8 Assessment of the predictive validity of classification functions

In order to asses the validity of the classification results, we need classify *a priori* additional cases, which were not used for the model construction. We can include or exclude cases from the analysis. Hence, the classification matrix can be computed for "old" and also "new" cases. Just after the classification of new cases it's possible to make conclusion about the validity of the classification functions. The classification of old cases only helps to identify outliers or "gray" areas where the classification functions are not performing well.

4. THE EMPIRICAL STUDY

4.1 Selection of the sample

The information about “bad” and “good” credit borrowers was gathered for the period from the year 2001 until the beginning of 2005. To build the initial credit scoring model this information was collected from the Area Managers of FcA. Credits applications of good and bad customers were selected from the FcA archive. In total, I have selected the initial sample of 1037 companies from 13 countries. After the careful consideration this sample was decreased to 862 companies[13], due to the fact that some applications were incomplete or for their assessment previous version[14] of the FcA credit scoring model was used.

4.1.1 Definition of “good” credit

The next criteria were used for the selection of “good” customers from the FcA database:

(1) the last payment was done not later than 2003-01-01,
(2) a customer did already at least 8 credit payments to FcA,
(3) customer’s indebtness to FcA is not more than 300 Euro according to the +30-list[15] ,
(4) total weighted number of days late is not more then 3 days[16].

The list of “good” customers was obtained by the observation of all payments for all customers.

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[13] See Appendix III
[14] Some credit applications were analyzed by the old version of FcA credit scoring model. In order to be consistent, I’m using for the building of a new credit scoring model credit applications of the companies , which were assessed by the last version of the FcA credit scoring model, which was created in the end of 2001
[15] The +30-list is the list of customers who have indebtness by the current credit payments more than 30 days. The sum 300 Euro was selected in order don’t allow bank’s service costs affect companies which were filtered out as good ones
[16] The algorithm of total weighted number of days is explained in Chapter 4.1.1.1

The list of “good” customers was filtered out in the next sequence of operations with the help of database management tools:

(1) all companies with the last date of payment not less then 2003-01-01[17],
(2) all customers who hadn’t made at least 8 payments in total in all open contracts with FcA were filtered out from the list created on the stage 1,
(3) all customers who had more than 300 Euro indebtness to FcA on the +30-list were filtered out from the list created on the stage 2,
(4) all customers with the total weighted number of days less than 3 days were filtered out from the list created on the stage 3.

4.1.1.1 Problem of the calculation of the total weighted number of days late in payments

The approach to calculate the total weighted number of days late in payments was suggested by FcA’s manager in order to make the selection criteria for “good” group more rigorous.

When we had started to follow this algorithm of “good” credit application finding, we faced with the problem what to do if a customer made some of its payments earlier than their due dates and some credit payments were made with delays. How we can treat this customer? It was suggested by FcA’s managers to consider also a money value of the each particular credit payment transaction, not only the time of payment. Below you can see the following example of their reasoning:

[17] The date 2003-01-01 was chosen due the technical specifications of the FcA database

N	Days late for the credit payments	Paid amount (€)	Share of payment in total sum of payments	Weighted number of days late
1	5	1200	13,00%	0,65
2	12	578	6%	0,72
3	3	7426	80%	2,4
4	27	133	1%	0.27
	Total sum of payments	**9337**	100%	
	Total weighted number of days late[18]			**4,04**

Table 1: Total weighted number of days late in payments - Example 1

The sum of the each payment transaction and the time of payment were taken into account. In the provided example you can see that the weighted number of days late is more if we received 7426€ with the delay of 3 days than when we got the payment of 133€ with the delay of 27 days.

Sometimes FcA's customers are making credit payments in advance (Table 2: Example 2). In this case, we have a negative number of days late for the credit payments, because customer made the first payment 10 days earlier than the due date. And the second payment was made with delay of 10 days. Total weighted number of days late is 0 in this case, and this customer is considered by our algorithm of selection as "good".

[18] Weighted number of days late = Days late for the credit payments * Share of payment in total sum of payments

N	Days late for the credit payments	Paid amount (€)	Share of payment in total sum of payments	Weighted number of days late
1	-10	1000	50%	-5
2	10	1000	50%	5
	Total sum of payments	**2000**	100%	
	Total weighted number of days late			**0**

Table 2: Total weighted number of days late in payments - Example 2

This algorithm has one important drawback that a customer, who is paying in advance, is considered as "good". In reality, there should be other reasons for an early payment, for instance, customer's desire to spend an excess of cash on hand or some seasonal fluctuations of payments.

When we have calculated the total weighted number of days late, we did not separate the payments by contract, only by customer. All payments value dates made by a customer where compared to their respective due dates irrespectively of which contract it was made for.

4.1.2 Definition of "bad" credit

The credit supposed to be "bad", if the history of relationships with the particular customer, who has bought commercial vehicles on credit, contains the one of the next historical facts:

(1) vehicles which were purchased on credit are repossessed,
(2) there were delays in credit payments more than 180 days,
(3) FcA brought a suit against this particular customer.

After having created both "bad" and "good" debt lists, FcA's Area Managers were asked to filter out customers that appeared on the lists mistakenly due to the technical errors[19] of the FcA's information system.

[19] Lists were not updated by managers in time

4.2. The variables for the multivariate discriminant analysis

After we have selected companies for "good" and "bad" groups, the data from credit applications of FcA's customers were collected. One of the important problems was to transfer information from the paper form into the digital format, which can be used by *STATISTICA* software. After the discussions with FcA's managers, 12 variables were selected from the initial set of 39. Among them were quantitative and qualitative ones.

Below, you can see the classification of these variables by next five categories.

General

1. Years in business (YrsB)
2. Hard Currency Income (HcInc)
3. Business Type (BusType)
4. Company's area of business (CompBus)
5. % of Sales Covered by Long Term Contracts (SalCvLnTrmCtr)

Liquidity

6. Current ratio (CurRt)
7. Solvency ratio (SolvRt)

Profitability

8. Gross Profit Margin (GpSales)

Activity

9. Growth Ratio of Fleet by number of units[20] in 3-years period (G3N)
10. Growth Ratio of Fleet by number of units in 5-years period (G5N)

[20] Here, we mean by unit one commercial vehicle. For instance, it can be a bus or a truck.

Debt Management

11. Repaid of Existing Financing (RpExFin)
12. Payment Record (PayRec)

These variables are considered by FcA managers as the most significant for their clients payment performance prediction. In Appendix I you can find their definitions and formulas for their calculations.

FcA managers initiated the variables #9 and #10 and I suggested using the formula for the Compound Annual Growth Rate (CAGR) as a method of these variables calculation:

$$CAGR = \left(\frac{Ending\_Value}{Beginning\_Value} \right)^{\left(\frac{1}{\#\_of\_years} \right)} - 1 \text{ ,} \qquad \textbf{[4.1]}$$

In our case, the formula [4.1] will be modified in the next two equations for 5 and 3 year periods, respectively:

$$\mathbf{G5N = ((FnT/InT_5)^{1/5}-1,} \qquad \textbf{[4.2a]}$$

and

$$\mathbf{G3N = (FnT/InT_3)^{1/3}-1,} \qquad \textbf{[4.2b]}$$

where G5N - Growth Ratio of Fleet by number of units in 5-years period,
G3N - Growth Ratio of Fleet by number of units in 3-years period,
FnT[21]- Final number of units in fleet,
InT_5 – Initial number of units in fleet for 5-years period[22],
InT_3 – Initial number of units in fleet for 3-years period[23].

[21] FnT = Current number of units in a customer's fleet + Requested number of units in a new credit application
[22] When the initial number of units for the considered period of 5 years is equal to 0, I assume InT equals to 0,1 in order to be able to calculate the Growth Ratio of Fleet.
[23] When the initial number of units for the considered period of 3 years is equal to 0, I assume InT equals to 0,1 in order to be able to calculate the Growth Ratio of Fleet.

These ratios give us an opportunity to get a picture of the fleet extension for FcA's customers. For instance, we have a customer (Table 3: Example 1) who had just 1 unit five years (InT_5=1) ago and 3 units three years ago (InT_3=1), and decided to receive a credit for 2 new additional units. In this case the expected final number of units for this customer (FnT) equals to 5 .Therefore, G3N = 37,97% and G5N = 18,56%.

Number of units	**2001**	**2002**	**2003**	**2004**	**2005**
Example 1	1	1	3	3	5
Example 2	1	2	3	3	15

Table 3: Fleet extension calculation – Example 1 & Example 2

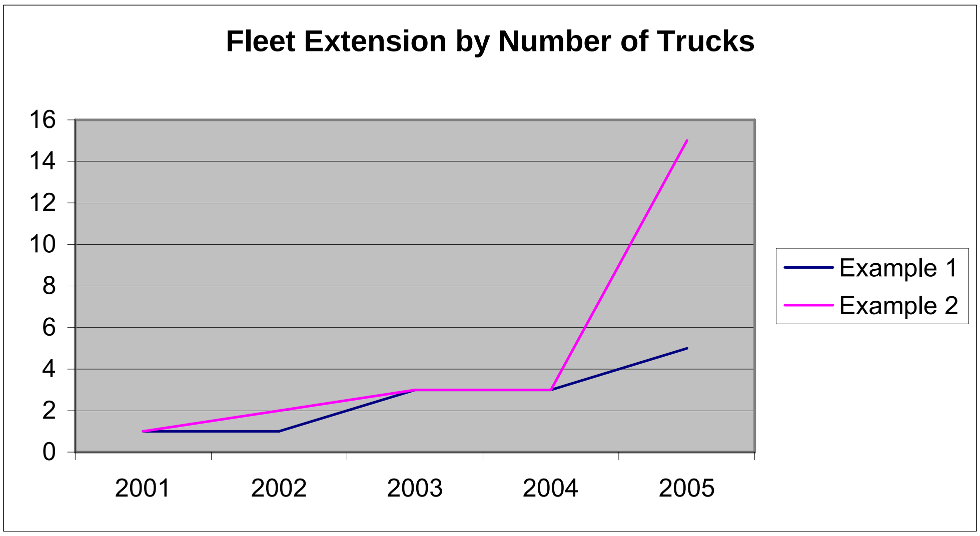

Figure 1: Fleet Extension by number of units

In contrast, we can have more extreme situation (Example 2), when another customer had also just 1 unit five years (InT_5=1) ago and 3 units three years ago (InT_3=3) and decided to receive a credit for 12 new additional units (FnT=15). In this case we have G3N = 78,26% and G5N = 81,71%. Higher values of G3N and G5N should be considered as a red flag and there are three main reasons for that:

(1) companies don't have experience of operating big fleets and gradual growth of fleet should assure us that customers are getting more and more fleet operating experience,
(2) it's a common situation on the emerging markets, where there is offers shortage of qualified employees, in our case drivers and technicians,
(3) customers already have many another units bought on credit and new ones may be a very heavy burden for them to repay.

4.3 Development of the new credit scoring model for Romania

In the initial sample I had 862 "good" and "bad" companies from 13 countries[24] according to the conditions of selection described in Chapter 4.1. However, for Macedonia and Lithuania we had quite small sample. For Macedonia we had just 1 "bad" company and 20 "good" companies, 3 "bad" and 3"good" respectively. These quantities of companies are not enough for the performing of the MDA procedure, and the new credit scoring models for these countries were not generated.

I decided to provide the detailed description of the new credit scoring building for Romania, because Romanian sample consists of 344 companies and is the biggest one.

4.3.1 Selection of the final sample

From the initial Romanian sample of 344 companies, I have selected companies in the period from 2002 to 2005 in order to have the similar macro economical conditions, which were remarked by the strengthening of Romanian Leu, and decreased level of inflation. In this period, we have 62 "bad" and 201 "good" companies. The size of this sample is sufficient for the credit scoring model building, for instance, Altman (1968) used 66 (33 "good" and "33" bad) companies and according to Moody's (2000) the samples medians of the similar empirical studies provided in the period of 1932 - 2000 were 45 for "good" companies and 40 "bad" companies respectively. Because of that reasons, the new credit scoring models for Lithuania and Macedonia

[24] See Appendix III

were not built.On the Figure 2 you can see the process of credit scoring model development and accuracy testing.

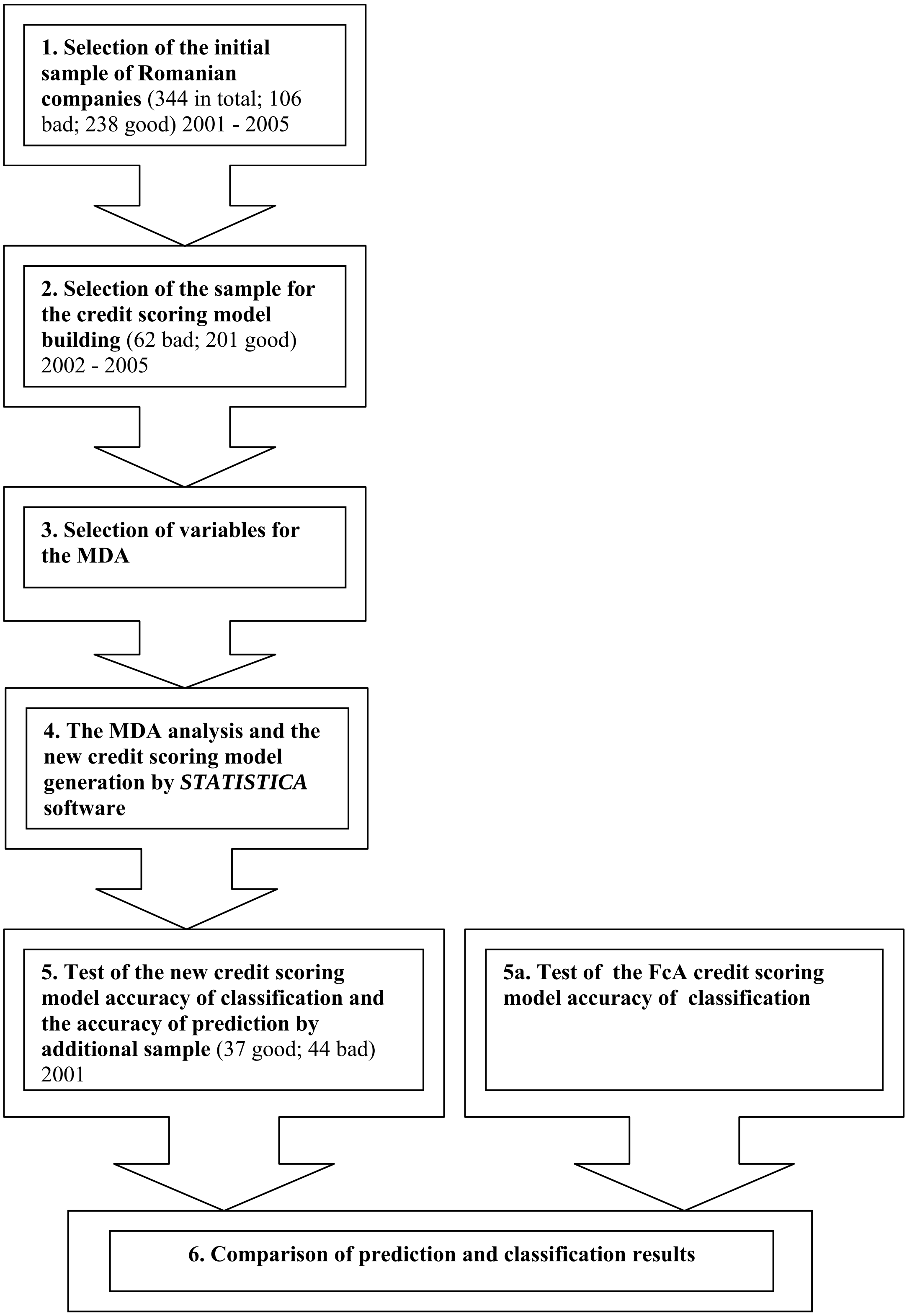

Figure 2: Process of credit scoring model development and accuracy testing

4.3.2 Selection of variables for the MDA

Values of all 12 selected variables were taken from the FcA credit applications. And then these variables were converted to the *STATISTICA*'s data format.

Before starting the final the MDA, I have tested the descriptive statistics of initial set of 39 variables with FcA managers and provided preliminary series of the MDA. The preliminary results of the MDA have shown us that some of the variables could not be used in the credit scoring model. The MDA has demonstrated that we have some discriminant variables with high discrimination power (high F-value) between "good" and "bad" groups, but with no logical connection between each other ("nonsense" statistics).

For instance, Management Rating (ManRate) is a qualitative variable showing the level of the company's management assessed by FcA Area Managers. In the preliminary the MDA this variable had negative impact on "good" group. High values of Management Rating are dominating in "bad" group. If we decide to use this variable in the model, it means that a customer with ManRate equaling to 3 ("Good, seems to be capable in their role") is more risky, for instance, than a customer with ManRate equaling to 0 ("The customer is not visited by FcA"). According to the manager's evidences, this situation is untrue. Hence, we can conclude that the high level of ManRate should be taken into the consideration of applicant's creditability very accurately and it is better to exclude this variable from the MDA.

Finally, I have got the list of 12 variables for the MDA in order to build the credit scoring model for the Romanian market:

1. Company's area of business (CompBus)
2. Years in business (YrsB)
3. Hard Currency Income (HcInc)
4. Business Type (BusType)
5. Sales Covered by Long Term Contracts (SalCvLnTrmCtr)
6. Current ratio (CurRt)
7. Solvency ratio (SolvRt)

8. Gross Profit Margin (GpSales)
9. Growth Ratio of Fleet by number of units in 3-years period (G3N)
10. Growth Ratio of Fleet by number of units in 5-years period (G5N)
11. Repaid of Existing Financing (RpExFin)
12. Payment Record (PayRec)

4.3.3 The MDA and the new credit scoring model generation

As it was explained before, I did the MDA analysis with the help of *STATISTICA* software in order to derive a linear combination of variables with canonical coefficients that give us the best discrimination between "good" and "bad" groups.

To perform the MDA , the forward stepwise analysis was chosen. The forward stepwise analysis helps not include insignificant variables in the model and also give us an opportunity to see what is going on each step of this analysis performing. *STATISTICA* is entering variables into the discriminant function model one by one, constantly choosing the variable that makes the most significant contribution to the discrimination.

During the forward stepwise analysis, *STATISTICA* is keeping the next rules to stop the analysis procedure:

(1) All variables have been entered, or
(2) The maximum number of steps has been reached[25] , or
(3) No other variable that is not in the model has an F-value greater than the specified F to enter[26], or
(4) Any variable after the next step would have a tolerance value that is smaller than specified in the model settings[27].

---

[25] The maximum number of steps is equal to the number of analyzed variables by default. In our case, it's equal to 12

[26] In my analysis the F to enter is equal to 1 (the value by default)

[27] I have used the value of the tolerance that was equal to 0.10. It means that variables, which are more than 90% redundant with other variables ,will not be included in the model

The F-value determines the extent to which a variable makes a single contribution to the prediction of group membership.

Here you can see the description of the each step in the forward stepwise analysis provided by *STATISTICA*:

```
 Stepwise Analysis - Step 0[28]
  F to enter: 1.000000    F to remove: 0.000000    Min.
Tolerance: .0100000
  Number of variables in the model: 0
  Wilks' Lambda: 1.000000


  Stepwise Analysis - Step 1
  F to enter: 1.000000    F to remove: 0.000000    Min.
Tolerance: .0100000
  Number of variables in the model: 1
  Last variable removed: PayRec   F (  1,    262) = 51.17670
p < .00000
  Wilks' Lambda: .8360650   approx. F (  1,    261) = 51.17669
p < .00000


  Stepwise Analysis - Step 2
  F to enter: 1.000000    F to remove: 0.000000    Min.
Tolerance: .0100000
  Number of variables in the model: 2
  Last variable removed: RpExFin   F (  1,    261) = 19.37084
p < .00002
  Wilks' Lambda: .7780944   approx. F (  2,    260) = 37.07484
p < .00000


  Stepwise Analysis - Step 3
  F to enter: 1.000000    F to remove: 0.000000    Min.
Tolerance: .0100000
  Number of variables in the model: 3
  Last variable removed: SalCvLnTrmCtr   F (  1,    260) =
10.87684   p < .00111
```

[28] Step 0 means that no variables are included in the model

```
  Wilks' Lambda: .7467349   approx. F (  3,    259) = 29.28110
p < .00000


  Stepwise Analysis - Step 4
  F to enter: 1.000000    F to remove: 0.000000    Min.
Tolerance: .0100000
  Number of variables in the model: 4
  Last variable removed: HcInc   F (  1,    259) = 3.286483
p < .07101
  Wilks' Lambda: .7373424   approx. F (  4,    258) = 22.97632
p < .00000


  Stepwise Analysis - Step 5
  F to enter: 1.000000    F to remove: 0.000000    Min.
Tolerance: .0100000
  Number of variables in the model: 5
  Last variable removed: GpSales   F (  1,    258) = 5.008911
p < .02607
  Wilks' Lambda: .7232464   approx. F (  5,    257) = 19.66845
p < .00000


  Stepwise Analysis - Step 6
  F to enter: 1.000000    F to remove: 0.000000    Min.
Tolerance: .0100000
  Number of variables in the model: 6
  Last variable removed: CurRt   F (  1,    257) = 1.797697
p < .18118
  Wilks' Lambda: .7182030   approx. F (  6,    256) = 16.74086
p < .00000


  Stepwise Analysis - Step 7
  F to enter: 1.000000    F to remove: 0.000000    Min.
Tolerance: .0100000
  Number of variables in the model: 7
  Last variable removed: CompBus   F (  1,    256) = 1.107109
p < .29370
```

```
  Wilks' Lambda: .7150983   approx. F (  7,    255) = 14.51347
p < .00000


  Stepwise Analysis - Step 7 (Final Step)
  F to enter: 1.000000    F to remove: 0.000000    Min.
Tolerance: .0100000
  Number of variables in the model: 7
  Last variable entered: CompBus   F (  1,    255) = .8123783
p < .36827


  Wilks' Lambda: .7150983   approx. F (  7,    255) = 14.51347
p < .00000
```

When the forward stepwise analysis is finished, *STATISTICA* provides us the table of the forward stepwise analysis results (Table 4). This table shows individual statistics for variables which were entered at the each step during the Stepwise analysis.

	Step	**F to enter**	**df 1**	**df 2**	**p-level**	**No. of vars. in**	**Wilk's Lambda**	**F-value**	**df 1**	**df 2**	**p-level**
PayRec	1	51.1767	1	261	0	1	0.836065	51.17669	1	261	0
RpExFin	2	19.37084	1	260	0.000016	2	0.778094	37.07484	2	260	0
SalCvLn TrmCtr	3	10.87684	1	259	0.00111	3	0.746735	29.2811	3	259	0
GpSales	5	5.00891	1	257	0.026074	5	0.723246	19.66845	5	257	0
HcInc	4	3.28648	1	258	0.071015	4	0.737342	22.97632	4	258	0
CurRt	6	1.7977	1	256	0.18118	6	0.718203	16.74086	6	256	0
Comp Bus	7	1.10711	1	255	0.293707	7	0.715098	14.51347	7	255	0

Table 4: Summary of Stepwise Analysis

Table 4 provides the following information:

1. the step number,
2. the F to enter,
3. the respective degrees of freedom for that F-value,

4. the *p*-level for that *F*-value,
5. the number of variables in the model after the respective step,
6. the overall value of Wilk's *Lambda* after the respective step,
7. the *F*-value associated with the *Lambda*,
8. the degrees of freedom for that *F*-value,
9. the *p*-level for that *F*-value.

Table 5 indicates the final statistics for the overall model created as a result of discriminate analysis by *STATISTICA*. This table gives information about the independent contributions for each variable to the overall discrimination between "good" and "bad" customers in the final model.

Step 7, N of vars in model: 7; Grouping: Status (2 grps)
Wilks' Lambda: .71510 approx. F (7,255)=14.513 p< .0000

	Wilks' Lambda	**Partial Lambda**	**F-remove -1,255**	**p-level**	**Toler.**	**1-Toler. (R-Sqr.)**
PayRec	0.886945	0.806249	61.27937	0	0.547656	0.452344
RpExFin	0.771622	0.926747	20.15594	0.000011	0.551426	0.448574
SalCvLn TrmCtr	0.752766	0.949961	13.43201	0.000301	0.943087	0.056913
HcInc	0.735594	0.972137	7.30871	0.007324	0.732611	0.267389
GpSales	0.724664	0.9868	3.41103	0.06592	0.691091	0.308909
CurRt	0.719862	0.993383	1.6986	0.193647	0.98773	0.01227
CompBus	0.718203	0.995677	1.10711	0.293707	0.863509	0.136491

Table 5: Discriminant Function Analysis Summary

Wilks' Lambda is the standard statistic that is used to denote the statistical significance of the discriminatory power of the model that will result after removing the respective variable. Wilks' Lambda can assume values in the range of 0 (perfect discriminatory power) to 1 (no discriminatory power).

Partial Lambda is associated with the unique contribution of the respective variable to the discrimination between groups. Partial Lambda of 0.0 denotes perfect discriminatory power. Therefore, the lower the value of Partial Lambda, the greater is the unique discriminatory power of the respective variable.

The F-to enter is associated with the respective Partial Lambda. Partial Lambda can be converted to a standard F value and the corresponding p-levels can be computed for each F.

The tolerance value of a variable is calculated as 1 - R-square of the respective variable with all other variables in the model. At each step of the stepwise analysis, *STATISTICA* generates the multiple correlation (R-square) for each variable with all other variables that are currently included in the model. As a result, the tolerance is a measure of the respective variable's redundancy. For instance, a tolerance value of 0,1 means that the variable is 90% redundant with the other variables in the model.

4.3.4 Canonical Analysis

The next task was to compute the actual discriminant functions in order to see how the five variables discriminate between "good" and "bad" groups of applicants.

STATISTICA provided results of the Chi square test of successive roots to show which discriminant canonical function gives better discrimination, but in our case, we have just two groups for classification. Hence, we have just one canonical discriminant function. This spreadsheet reports a step-down test of all canonical roots. The first line contains the significance test for all roots; the second line reports the significance of the remaining roots, after removing the first root, and so on. Therefore, this Chi square test of successive roots tells you how many canonical roots (discriminant functions) to interpret.

Roots Removed	**Eigen-value**	**Canonicl R**	**Wilks' Lambda**	**Chi-Sqr.**	**df**	**p-level**
0	0.398409	0.533762	0.715098	86.34883	7	0

Table 6: Chi-Square Tests with Successive Roots Removed

The table above contains the significance test for all roots. Therefore, this Chi square test of successive roots tells how many canonical roots (discriminant functions) is required to interpret.

When extracting the canonical roots, *STATISTICA* is also computing the *eigenvalues*. The *eigenvalues* can be interpreted as the proportion of variance accounted for by the correlation between the respective canonical variates. The proportion (Cum.Prop) is computed relative to the variance of the canonical variates or, if to put it differently, the variance of the weighted sum scores of the two sets of variables. The *eigenvalues* do not let you know how much variability is explained in either set of variables, but using *STATISTICA*, we can compute as many *eigenvalues* as there are canonical roots or, in other words, as many as the minimum number of variables in either of the two sets.

We can also test the null hypothesis that the observations come from the same population for "good" and "bad" groups by calculating the Means of canonical variables.Obtained results are summarized in the table. Hence, I can reject the null hypothesis that the observations come from the same population. We can conclude that "good" and "bad" groups are significantly different from each other and it is possible to implement the MDA.

	Root 1
Bad	0.34922
Good	-1.13216

Table 7: Means of Canonical Variables

Also we got the Coefficients for canonical variables which we need to use in our model for the Z-score calculation. The next table presents the Raw Coefficients spreadsheet.

	Root 1
PayRec	-1.12181
RpExFin	3.15191
SalCvLnTrmCtr	-1.1962
HcInc	-0.97943
GpSales	0.94343
CurRt	0.03113
CompBus	-0.07256
Constant	1.98845
Eigenval	0.39841

Table 8: Raw Coefficients for Canonical Variables

The Raw Coefficients can be used in combination with the observed data to compute (raw) discriminant function scores. Observed data are provided in the Appendix IV.

The Z-scores for each company in the sample are provided in the Appendix IV. You can see that “good” companies have the positive sign of the Z scores and “bad” companies have the negative sign.

The canonical discriminant function below has the most significant variables that were selected by the Stepwise method [29] provided by *STATISTICA*:

Z-score $_{\text{Romania 02/05}}$ = -1.12181*PayRec + 3.15191*RpExFin -1.1962 SalCvLnTrmCtr-0.97943*HcInc+ 0.94343*GpSales +0.03113*CurRt - 0.07256* CompBus + 1.98845, **[4.3]**

where PayRec – Payment Record,
RpExFin – Repaid of Existing Financing,
SalCvLnTrmCtr- % of Sales Covered by Long Term Contracts
HcInc – Hard Currency Icome,
GpSales - Gross Profit Margin,
CurRt – Current Ratio,
CompBus - Company’s area of business,
1.98845 - Constant

Payment Record (PayRec) is a qualitative parameter estimated by mangers basing on the FcA payment database. If this variable is big, it means a bad payment performance – payment with delays or non-payment at all[30].

Repaid of Existing Financing (RpExFin) is a quantitative variable that shows us which share of an existing financing is already paid by customer. High value of this ratio means that our customer is a reliable payer who almost already paid his previous obligations and ready to get a new credit.

[29] See Chapter 3.2
[30] See Appendix II

Hard Currency Income (HcInc) is a quantitative variable, which give information about share of hard currency income in total customer's income. In this research work we can see the interesting phenomena that high hard currency income has negative impact on Romanian companies in the period of 2002-2005.It should be explained by the Romanian Leu appreciation against the Euro, which is the most common currency of income for Romanian unit operators, during the last two (Appendix VI). The growth of Romanian Leu against Euro in the period from September of 2004 to June 2005 was about 14%[31].

Current Ratio (CurRt) is well known indicator of company's solvency ratio that indicates ability of a company to cover current debts by total current assets. If this ratio is rising, it is positive trend. Our derived equation is coinciding with this statement.

Gross Profit Margin (GpSales) is also widely used in the financial world measure of company's efficiency, which gives us information about the profits earned for each dollar of sales. Growing Gross Profit Margin ratio is a positive trend.

Sales Covered by Long Term Contracts (SalCvLnTrmCtr) shows us the percentage of applicant's contracts, which are covered by long-term contracts. This ratio shows to credit controller how reliable applicant's business prospective. In our case this ratio has high discriminate power and negative impact on "good" group also. We can explain it by uncertainty of business prospective for some Romanian companies – inability to predict real share of sales covered by long term contracts. Also the negative impact of this ratio should be explained by unclear definition of the term "long-term contract" and also by the evidence that Romanian companies without long-term contracts are able to be more profitable having just short-term contracts due to the skills of management and high turnover.

[31] ROL/EUR Sep 2004 = 41127; ROL/EUR June 2005 = 36050 (Data provided by Romanian Central Bank)

Company's area of business (CompBus) is a qualitative parameter showing us to which particular category of business areas an applicant belongs. You can see the index of business areas in the Appendix II.

After we have determined the canonical coefficients of the descriminant function for the new credit scoring model, we can calculate the Z score for each company in the sample and also for the new companies, which are not in the sample. The higher the Z- score, the better the company looks from the perspective of default. Here is an interpretation:

Z=0 (Constant from the equation above): 50-50 probability of future bankruptcy,
Z<0: There is more than 50 percent probability of bankruptcy,
Z>0: There is less than 50 percent probability of bankruptcy.

On the Figure 3 you can see the distribution of the Z-scores calculated by the derived discriminant canonical function for “good” and “bad” groups. After we have calculated the Z-score for each company, we can calculate the probability of default considering that the Z-score represents the number of standard deviations from the grand centroid[32]. In our case, I assume that the grand centroid is equal to 0.Thus, if the company has Z= 1 the probability of default for this company is equal to one standard deviation σ in positive direction from the grand centroid. Basing on the diagram depicted on the Figure 3 of the overall Z-score distribution, I can assume that the Z-scores for “good” and “bad” companies are normally distributed and, for instance, companies with Z=1 have probability of default which is approximately equal to 18%[33].

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[32] Grand centroid is the point representing the mean of the Z - scores for all companies in the sample

[33] P_{df} =1-0,50 – 1σ = 1 – 0,50 – 0,325 = 18%

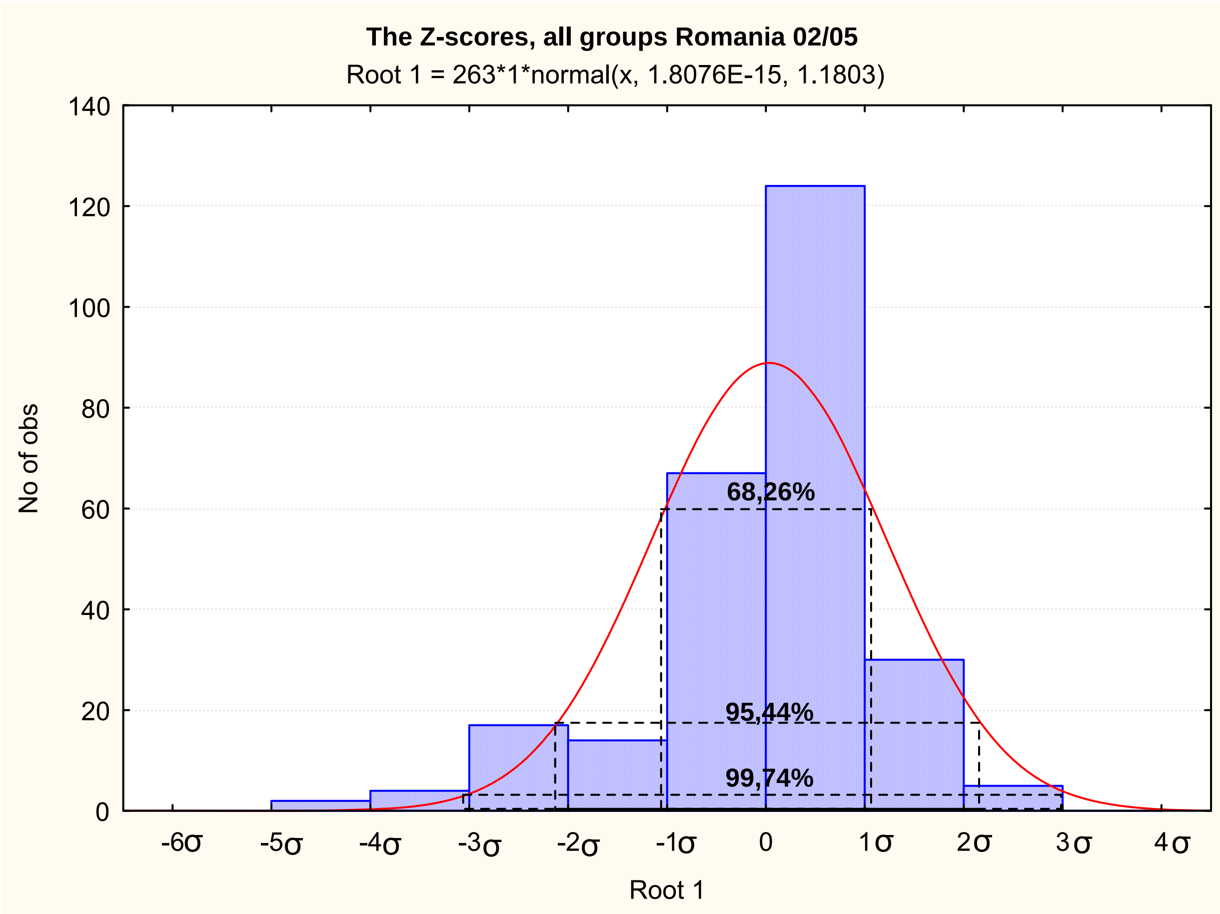

Figure 3: The Z-scores overall distribution for the Romanian sample 2002-2005

After deriving the discriminant function [4.3] and determining its overall discriminating power, it is possible to calculate the Z-score for any new company that we want to assess as to its potential default. It can be done by multiplying the actual variable value by its discriminant coefficient and summing the five products.

For instance, the Z-score for Company № RO5 (Appendix IV) is -1.63164 and is calculated by the next equation:

Z-score $_{RO5}$ = -1.12181*3[34] + 3.15191*0.31 - 1.1962*0.8 - 0.97943*0.8 + 0.94343*0.67 + 0.03113*3.03 - 0.07256* 3 + 1.98845 = -1.63164, [4.4]

[34] For the calculation of the Z-scores we are using the unique numerical equivalents generated by *STATISTICA* software for the qualitative variables CompBus and PayRec. See Appendix II.

№	Comp Bus	Hc Inc	SlCvLnT Ctr	Gp Sales	Cur Rt	RpEx Fin	Pay Rec	Status
RO5	3	0.8	0.8	0.67	3.03	0.31	3	Bad

On the following figure, you can see graphical results of the Z-scores distribution of Romanian sample for 201 "good" and 62 "bad" companies.

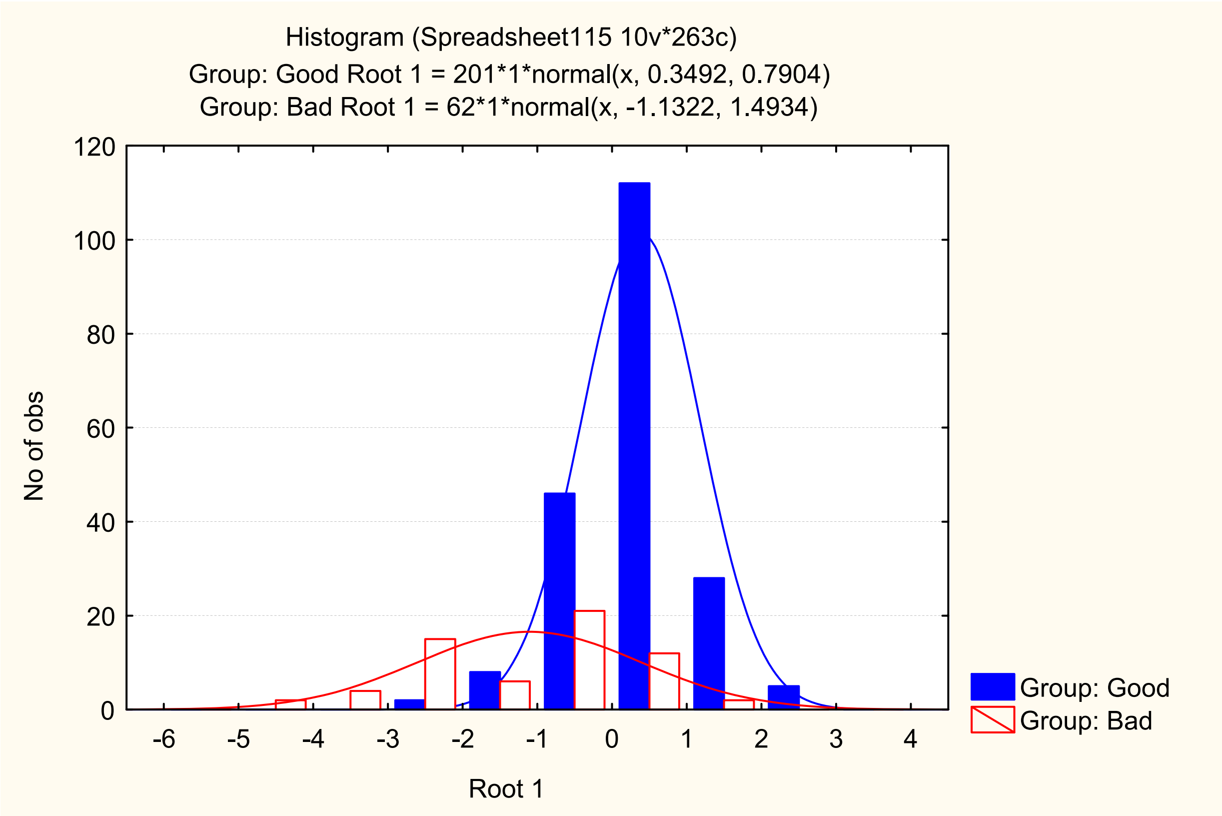

Figure 4: The Z-scores distribution of Romanian sample for 201 "good" and 62 "bad" companies

4.3.5 Group Classification and Types of Errors

Altman (1968) illustrates the format for presenting the results of the MDA model's predictive ability as the following chart ("accuracy matrix"):

		Predicted Group Membership	
		Bankrupt	**Non-Bankrupt**
Actual Group Membership	**Bankrupt**	H	M1
	Non-Bankrupt	M2	H

where H – correct classifications (Hits),

M1 – a Type I error,

M2 – a Type II error.

Table 9: Accuracy matrix

The actual group membership is equivalent to the *a priori* classification[35] and the model tries to classify correctly the companies between groups. The model's nature at this stage is explanatory, but when we are classifying new companies, the nature of the model is becoming predictive.

The sum of the diagonal elements H's divided by the total number of companies being classified, gives the measure of total accuracy of the MDA in classifying firms. This measure is similar to the coefficient (R^2) in regression analysis, which assesses the percent of the variation of the dependent variable explained by the independent variables.

Assessing the accuracy of the model, we need to take into the consideration the different costs of errors. The Type I error is made when a which becomes "bad" customer is classified as "good"; the Type II error is when "good" company is considered as "bad". The Type I error is more costly for FcA, because it means that a credit is granted to the company which ultimately defaults; the Type II error arises when a company's credit application is not approved, in spite of the companies ability to meet its credit obligations successfully. The Type I error is associated with the next possible costs:

(1) lost of interest income and/or,
(2) partial/or complete loss of the principal,

[35] The computations for the classification of cases provided by *STATISTICA* are based on the a priori classification probabilities that are either (1) the same for all groups, (2) proportional to the respective group sizes, or (3) user defined .

(3) time spent by FcA executives and credit managers in the collection phase,
(4) legal fees,
(5) opportunity cost of income on the interest and principal not repaid which could have been earned on the alternative credit.

The costs of the Type II error are significantly less than associated with the Type I error. If a “good” customer was considered as “bad” then the next costs are possible:

(1) lost of interest income (the difference between the rate that would have been charged and some risk-free rate)[36],
(2) opportunity cost of income on the interest and principal which could have been earned.

In this paper, I decided to use the same approach for presenting as it was suggested by Altman, but with the next modifications:

		Percent Correct	**Predicted Group Membership**	
			Bad	**Good**
Actual Group Membership	**Bad**	% accuracy of “bad” prediction	H	M1
	Good	% accuracy of “good” prediction	M2	H
	Total	% total accuracy of the model		

Table 10: Modified accuracy matrix

[36] This loss of interest is zero if there is an opportunity for FcA to invest with return income comparable with the interest that would have been charged on the denied credit application.

4.3.5.1 Classification functions

STATISTICA software also has provided the classification functions for each group. The next spreadsheet containing the classification functions was displayed as the new model was built:

	Good p=.76426[37]	**Bad p=.23574**
PayRec	1.57052	3.2324
RpExFin	-0.98181	-5.651
SalCvLnTrmCtr	2.11084	3.8829
HcInc	-0.125	1.3259
GpSales	7.7399	6.3423
CurRt	0.05565	0.0095
CompBus	1.64034	1.7478
Constant	-6.45175	-11.1535

Table 11: Classification functions coefficients

Classification functions are computed for each group and can be used directly to classify cases:

Z good = 1.57052*PayRec - 0.98181*RpExFin + 2.11084* SalCvLnTrmCtr - 0.125*HcInc + 7.7399*GpSales + 0.05565*CurRt + 1.64034 CompBus - 6.45175 ,

[4.5a]

Z bad = 3.2324*PayRec -5.651*RpExFin + 3.8829* SalCvLnTrmCtr + 1.3259*HcInc + 6.3423*GpSales + 0.0095*CurRt + 1.7478CompBus - 11.1535

[4.5b]

[37] *A priori* classification probabilities were set proportionally to the size of each group.

We would classify a case into the group for which it has the highest classification score.

4.3.5.2 Classification matrix for the original sample

The classification matrix for the original sample (201 “good” and 62 “bad” companies) contains information about the number and percent of correctly classified cases in each group.

	% Correct	Bad	Good
Bad	37%	23	39
Good	97%	6	195
Total	83%	29	234

Table 12:Classification matrix for the original Romanian sample

	No. Correct	% Correct	% Error	n
Type I	23	37%	63%	62
Type II	195	97%	3%	201
Total	218	83%	17%	263

Table 13: Classification matrix for the original Romanian sample (Type I and Type II Errors)

The new model was accurate in classifying of 83% of the companies of the original sample. The Type II error was at 3% and Type I error was at 63 % .This is better than a pure chance model. But we need to concern this result critically, because the companies were classified by the discriminant functions which were based on the individual data of these same companies.

4.3.5.3 Prediction accuracy test for new model

In order to verify the reliability of the new model built on the original sample of data, the second sample of 81 Romanian companies was used (Appendix

XVIII). The data of these companies was not used in the new model generation[38], and it helps to avoid the potential bias in classifications.

	% Correct	Bad	Good
Bad	75	33	11
Good	40	22	15
Total	59	55	26

Table 14: Classification matrix for the additional Romanian sample

	No. Correct	% Correct	% Error	n
Type I	33	75%	25%	44
Type II	15	40%	60%	37
Total	48	59,2%	40,8%	81

Table 15: Classification matrix for the additional Romanian sample (Type I and Type II Errors)

The new model has shown superior results in the Type I error prediction. An explanation of these results compared to the initial results may be minor sampling errors in the original sample and search bias to selecting variables for the MDA. In addition, we can say that the new model for the Romanian market has very rigorous requirements for credit applicants in order to get status of "good" company. The results of Type II error prediction for the additional sample are quite low (just 40% are correct).

4.3.5.4 Posterior probabilities

In the Appendix VI the posterior probabilities of the belonging to the particular groups for the original sample are calculated on the base of Mahalanobis distances and the *a priori classification probabilities*[39]. It is possible directly to compute the probability that a case belongs to a particular group. These probabilities are conditional, because they are dependant on knowledge of the

[38] The additional sample was selected from Romanian companies (year 2001). "Bad" 44 and "good" 37.

[39] I set the a priori probability proportionally to group sizes

values for the variables in the model. Hence, these probabilities are called *posterior*.

A case is classified into the group for which it has the highest posterior classification probability. Actual posterior probabilities for 201 “good” and 62 “bad” Romanian companies are provided in Appendix V.

4.4. Classification accuracy of the existing FcA credit scoring model and new credit scoring model

The existing FcA credit scoring model consists of 26 qualitative and quantitative variables. The FcA credit scoring model classifies all credit applications in the accordance to the possible level of risk by 4 categories, where “A” indicates the lowest level of risk and “D” indicates the highest.

To compare the accuracies of classification for the new credit scoring model and for the FcA credit scoring model, I decided to classify the same sample of 62 “bad” and 201 “good” Romanian companies that was used for the building of the new model, by the FcA credit scoring model. You can see the FcA credit rating for these companies in the Appendix IV.

Our main task is to check how accurately the FcA model is able to classify companies in the light of proportion of “bad” companies in each category. Ideally, this proportion must have increasing trend from A to D to cover increasing risks by the appropriate credit interest rate.

Romania 02/05 FcA rating	**Size of the sample**		**263**
	% of Bad	**Bad**	**Good**
A	0%	0	1
B	16%	10	55
C	81%	50	105
D	3%	2	40

Table 16: Accuracy of classification by the FcA credit scoring model

From the table above we can see misbalance of the FcA credit scoring model. Charged risk premiums are not optimal. In category B, it has 16% of total bad customers, and in category C, it has 81% respectively. It means that B and C customers are charged incorrectly (too small risk premium). In category D, customers are overcharged (too big risk premium).And it was also expected that the number of bad D customers is bigger than the number of bad C customers. In this particular situation, FcA does not have loss because of overcharged D customers. However, this situation is not so good from the position of market competitiveness. If D customers feel that they are overcharged, they should go to another financial organization with more attractive interest rates to get credit.

In order to test classification accuracy of the new credit scoring model, I used the same ranking as in the existing model, but with another interpretation. The new credit scoring model was calibrated using the following conditions of ranking:

(1) If The Z-score > 2, a company has rating A (very safe area),
(2) If 2>The Z-score > 1, a company has rating B (safe area),
(3) If 0<The Z-score < 1, a company has rating C (uncertain area),
(4) If The Z-score <0 , a company has rating D (dangerous area)

Hence, for the new credit scoring model we have the following results of classification:

Romania 02/05 New model rating	**Size of the sample 263**		
	% of Bad	**Bad**	**Good**
A	0%	0	5
B	3%	2	28
C	19%	12	112
D	77%	48	56

Table 17: Accuracy of classification by the new credit scoring model

Basing on the results of the classification accuracy by the new credit scoring model, we can say that FcA credit scoring model is not as accurate as the new one. The new credit scoring model helps to charge potential applicants more adequately. The biggest number of "bad" customer is among D category (the most risky) – 77%. C category has 19% of "bad" customer. In contrast, A category has no "bad" customers at all and B category has just 3% of total "bad" customers.

4.5 Power Analysis

As I emphasized before, we need to use additional cases, which were not used for the model construction, in order to asses the validity of the classification results of the new credit scoring model. We have obtained already the classification matrix for "old" cases. The classification of "old" cases only helps to identify outliers or "gray" (overlapping) areas where the classification functions are not performing well. For the purposes of the checking of the new credit scoring model accuracy, I have implemented the Power Analysis method that is supported by *STATISTICA* software.

The Power Analysis method is the technique that provides us solution for the next questions,(a) how large a sample is needed to enable accurate and reliable statistical judgments , (b) what is a likelihood of a given sample size effects detection by statistical test in a particular situation.

An implementation of The Power Analysis (The PA) gives us an opportunity to design the test of the model accuracy with the minimal sufficient number of new cases. The PA helps us to avoid the lack of the precision if the sample size of new cases is too low and the waste of resources if the sample of new cases is too large.

One goal of the PA is to test whether the proportion of events occurring in a population differs from a hypothesized value.We already have selected the total number of "bad" cases that equals to 106. Hence, we can calculate the Pi (the actual proportion) and the Pi0 (the null hypothesized proportion).

Consecutively, a Chi-square test was performed, with the Type I Error rate (alpha) set at 0.05.

This test is one-tailed (H0: Pi < Pi0), so that only a positive deviation from the hypothesized value could be declared significant.We assumed that, in the sampled population, the actual proportion Pi = 0.31, and the null hypothesized proportion Pi0 = 0.06.
In order to get the optimal sample size for the accuracy test of the new credit scoring model for Romania, *STATISTICA* software performed the PA, and the following results were obtained:

One Proportion, Z, Chi-Square Test
H0: Pi < Pi0

Null Proportion (Pi0)	0.0600
Population Proportion (Pi)	0.3100
Alpha (Nominal)	0.0500
Actual Alpha (Exact)	0.0673
Power Goal	0.9000
Actual Power (Normal Approx.)	0.8769
Actual Power (Exact)	0.9144
Required Sample Size (N)	16.0000

Table 18: Sample Size Calculation

So, we can conclude that to achieve the requested power of 90.00%, at least 16 observations are required. With N = 16, the actual power is 91.44%.

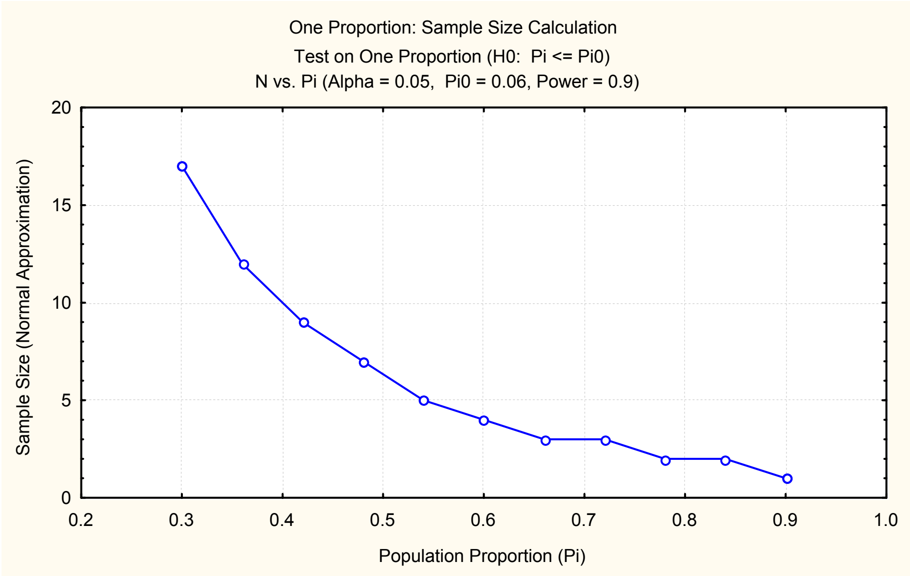

Figure 5: Sample Size vs. Population Proportion

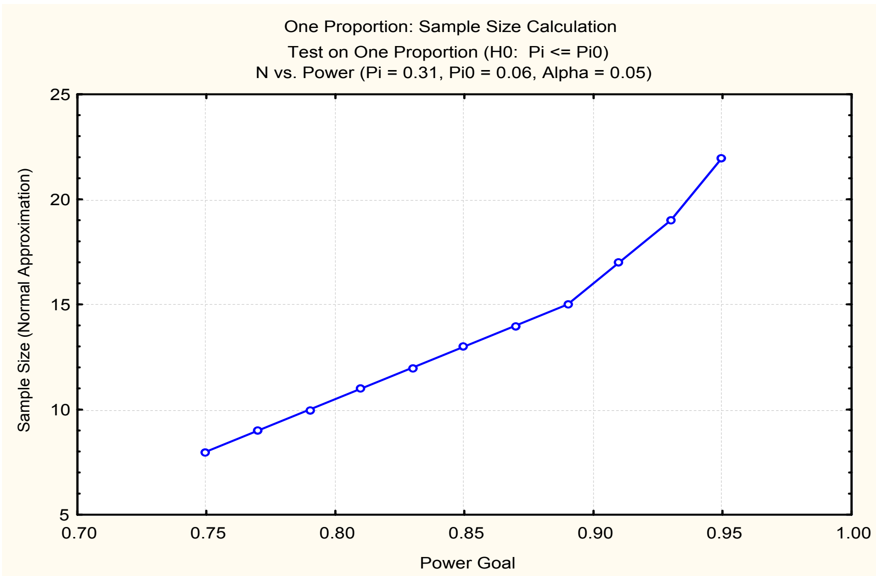

Figure 6: Sample Size vs. Power

We have selected randomly 16 additional Romanian companies in order to check the quality of the new credit scoring model. Unfortunately, we don't have additional "bad" Romanian companies for the model testing. And the additional sample was taken from the number of Romanian companies, which have average credit-payment performance. The main idea of this test was to check the coincidence of the new credit scoring model forecast and decisions made by FcA managers. If we have overwhelming majority classified companies as "bad" by the new credit scoring model, it might be considered as a lack of quality of the new credit scoring model. In this test we are getting the information about the size of Type II error – the situation, when "good" company is considered as a "bad" one.

Romania New Credit scoring Model	**Size of the sample** 16		
	Percent of Bad	Bad	Good
	37%	6	10

Table 19: Accuracy of additional Power analysis sample classification

Our findings for the 16 additional Romanian companies prove that the new credit scoring model makes high demands for the new applicants.

5. DEVELOPMENT OF THE NEW CREDIT SCORING MODELS FOR OTHER MARKETS

In Chapter 5, the results of the MDA analysis are provided for other emerging markets: Belarus, Bosnia, Bulgaria, Croatia, Indonesia, Latvia, Russia, Serbia & Montenegro, Turkey, and Ukraine. The process of the new credit scoring model development is analogous to the one already described for the Romanian market and the same set of 12 variables was used. The summarizing statistics will be provided for each emerging market.

Credit scoring models for Lithuania and Macedonia were not built due to limited data.

Power analysis of the new- credit scoring accuracy estimation was done just for the selected markets: Turkey, Ukraine, Serbia & Montenegro, Russia, Croatia and Romania. For the other emerging markets the additional data was not provided by FcA. The results of Power Analysis are provided in Appendix VIII– Appendix XVIII.

The results of the new credit scoring models development for other emerging markets are provided in Appendix VII – Appendix XVII.

6. COMPARISON OF OBTAINED MODELS

All variables from the canonical discriminant functions for each market[40] are summarized in Table 19, including the most significant[41] variables for all markets and the frequency of presence of the discriminant variables.
The new overall credit scoring overall model was generated with the help of *STATISTICA* software.

We can see that the most frequently used variable is RpExFin (Repaid of Existing Financing). RpExFin is used in all canonical discriminant functions (See Table 19) and it has 9 positions in the Top 5 lists (Table 20 and Table 21). This high frequency might be explained by the factor that it's really important for an applicant to have good credit history. Our analysis proves this reason.

SalCvLnTrmCtr (% of Sales Covered by Long Term Contracts) has 6 positions in the Top 5 lists and is used in 8 credit scoring models. However, this variable also has different effect [42]for some countries. Mainly it happens due to the differences in business approaches and management skills. In Romania we see that companies with a small share of sales covered by long term contracts are more successful. In Turkey and Russia the opposite is true.

PayRec (Payment Record) has 6 positions in the Top 5 lists and is used in 8 credit scoring models. Presence of this variable is also explainable, because payment records indicate payment performance. "Good" companies have better payment records than "bad" ones.

BusType (Number of business areas) has also 6 positions in the Top 5 lists and is used in 7 credit scoring models. Business diversification impact differs by

[40] See Appendix VIII
[41] Significance is determined by F-value. See Appendix VIII "the MDA and the new credit scoring model generation" section
[42] See Appendix VIII "Canonical Analysis" section for each country. You can see the impact by the sign of respective variable

countries. In Bulgaria it is the case that “good” companies have diversified businesses in contrast to Indonesia.

G5N (Growth Ratio of Fleet by number of units in 5-years period) has 6 positions in the Top 5 lists and is used in 8 credit scoring models. This ratio has different impacts for the emerging markets. For instance, “good” companies in Turkey and Indonesia extend their fleets very extensively and they have high value of G5N , but Russian and Ukrainian companies with high values of G5N are considered as more risky. It can be explained by a lack of experience among Russian and Ukrainian entrepreneurs in comparison with their Turkish and Indonesian colleagues. Russia and Ukraine have an experience of working in the conditions of market economics only 15 years, and it takes time for managers to get skills of a big fleet management in the environment of free market.

SolvRt (Solvency ratio) has 6 positions in the Top 5’s lists and is used in 8 credit scoring models. According to financial theory, it’s good to have this ratio at a high level. It’s derived by taking a company's net worth and dividing by total assets.

HcInc (Hard Currency Income) has 4 positions in the Top 5 lists and is used in 6 national credit scoring models. This variable has large discriminant power for Belarus, Croatia, Latvia, Romania and Turkey. But in the credit scoring model for Turkey this variable has a positive impact and for Romania it has a negative impact. This can be explained by the high annual inflation in Turkey and the fact that the Romanian Leu appreciated against the Euro during the last 2 years. Other possible reasons for the negative impact of HcInc are the absence of hedging financial instruments for the emerging markets and a possible lack of financial skills among managers to hedge potential exchange risks.

If we compare the accuracy of the new-credit scoring for each market with the new overall credit scoring model we can see in most cases that the national models are more accurate than the overall model. Hence, we can conclude that it’s more desirable to use national versions of credit scoring models instead of using the common overall credit scoring models. All emerging markets are quite different and that’s why it’s better to have customized versions of the credit scoring models that take into account differences in national economics, laws and regulations, and styles of doing business.

N	Variable	(1) Belarus	(2) Bosnia	(3) Bulgaria	(4) Croatia	(5) Indonesia	(6) Latvia	(7) Romania	(8) Russia	(9) Serbia	(10) Turkey	(11) Ukraine	*Frequency*	Overall model
1	**CompBus** (Company's area of business		1					1		1		1	4	1
2	**YrsB** (Years in business)	1			1					1		1	4	1
3	**HcInc** (Hard Currency Income)	1			1		1	1			1		5	1
4	**BusType** (Number of business areas)		1	1		1	1		1	1		1	7	1
5	**SalCvLnTrmCtr** (% of Long Term Sales)				1	1	1	1	1	1	1	1	8	1
6	**RpExFin** (Repaid of Existing Financing)	1	1	1	1	1	1	1	1	1	1	1	11	1
7	**PayRec** (Payment Record)	1	1			1	1	1	1		1	1	8	1
8	**GpSales** (Gross Profit Margin)					1	1	1		1			4	
9	**CurRt** (Current ratio)		1		1			1		1	1	1	6	1
10	**SolvRt** (Solvency ratio)	1		1	1	1	1		1		1	1	8	1
11	**G5N** (Growth Ratio of Fleet in 5-years period)	1	1	1		1	1		1		1	1	8	1
12	**G3N** (Growth Ratio of Fleet in 3-years period)			1	1							1	3	
	Total number of variables	6	6	5	7	7	8	7	6	7	7	10		10
	Accuracy of Bad (Type I Error)	57%	78%	71%	43%	100%	80%	37%	58%	40%	28%	63%		25%
	Accuracy of Good (Type II Error)	93%	78%	93%	89%	93%	96%	97%	87%	95%	98%	87%		94%
	Total Accuracy	81%	78%	89%	74%	95%	90%	83%	74%	84%	93%	76%		75%

Table 20: Comparison of the new credit scoring models

	TR	RU	BA	BG	BY	CS	HR	ID	LV	RO	UA
1	Rp ExFin	G5 num	G5 num	Solv Rt	Solv Rt	Bus Type	HcInc	G5 num	Pay Rec	Pay Rec	SolvRt
2	SalCv Ln Trm Ctr	Solv Rt	Rp ExFin	Bus Type	Rp ExFin	SalCv Ln Trm Ctr	Solv Rt	Rp ExFin	Solv Rt	Rp ExFin	Comp Bus
3	HcInc	Pay Rec	CurRt	Rp ExFin	HcInc	Gp Sales	Rp ExFin	Bus Type	Rp ExFin	SalCv Ln Trm Ctr	G5 num
4	Pay Rec	Bus Type	Bus Type	G5 num	YrsB	Rp ExFin	CurRt	Pay Rec	Bus Type	HcInc	G3 num
5	CurRt	SalCv Ln Trm Ctr	Comp Bus	G3 num	Pay Rec	Comp Bus	G3 num	SalCv Ln Trm Ctr	G5 num	Gp Sales	SalCv Ln Trm Ctr

Table 21: Top 5 variables for all emerging markets

N	Variable	Frequency
1	**RpExFin**	9
2	**SalCvLnTrmCtr**	6
3	**PayRec**	6
4	**BusType**	6
5	**G5num**	6
6	**SolvRt**	6
7	**HcInc**	4
8	**CompBus**	3
9	**CurRt**	3
10	**G3num**	3
11	**GpSales**	2
12	**YrsB**	1

Table 22: Frequency of variables in all Top 5 lists

N	Variable
1	**PayRec**
2	**RpExFin**
3	**G5num**
4	**BusType**
5	**SalCvLnTrmCtr**

Table 23: Top 5 variables of Overall model

7. SUMMARY AND CONCLUSIONS

The main purpose of this paper was to use the MDA statistical technique in order to build new credit risk models for emerging markets. Today's emerging markets are too complex to be characterized using simple financial ratios for the analysis of credit worthiness. That is why it is required to use new credit scoring models for the prediction of borrowers default. Modern developments in sophisticated statistical computer applications, as *STATISTICA*, have helped and increased the possibility for broader research development and practical implementation of credit risk models.

In this thesis the MDA has proved to be a robust technique in classifying credit risks into "good" and "bad" groups on 83% correct classification on average for all 11 emerging markets. Average accuracy of "bad" companies' classification (Type I Error) is 60% and average accuracy of "good" companies' classification (Type II Error) is 91%. Low levels of Type I Error prediction for some emerging markets can be explained by the fact that macroeconomic conditions in the emerging markets are very volatile and some local companies tend to manipulate data for credit applications. This statement can be suggested by the fact that there are a very small number of variables, which are financial ratios, among the most frequent ones in the Top 5 list (Table 21). Only variable SolvRt (Solvency Ratio), financial ratio, has relatively high frequency of 6 in this list.

Possible reasons that the new credit scoring models are not highly accurate for some markets include:

(1) absence of a sufficient number of "good"/ "bad" companies number[43],
(2) companies for the analysis were not taken from the same period of time[44],
(3) companies were not segmented by size of total assets,
(4) incomplete set of discriminant variables.

[43] It's good to have at least 30 companies for each group according to the research done previously. See Moody's (2000) p.14

[44] Companies were taken from the 5 year period 2001-2005

It is sensible to try new sets of discriminant variables to build more accurate credit scoring models. These new variables should not be taken from the company's books but should be qualitative in nature. For instance, it can be the region where companies are performing business activity inside a particular country or some new variables giving information about the quality of management in a particular company.

The new credit scoring model gives the opportunity to classify new applications by the level of risk more accurately in comparison with the existing FcA's credit scoring model. This comparison was provided for the Romanian market, but the same approach should be easily implemented for the rest of the markets. This capability of the new model is very important, because it gives FcA the opportunity to decrease significantly the level of Type II Error. The new credit scoring model helps to decrease the number of variables required for the evaluation of credit applications. The existing FcA's credit scoring model consists of 26 variables. In contrast, we can see that new credit scoring models have from 5 to 10 variables(Table 20).For example, the new credit scoring model for Bulgaria consists of 5 variables and gives the classification accuracy of 95%. The new credit scoring models, obtained in this thesis, help managers to save time required for credit applications evaluation by decreasing a number of variables for the analysis. Surely, it's not recommended to rely just on the new credit scoring models in situations, when big amounts of credits are provided or new customers are applying for a credit. In this case, it's better to make an additional thorough analysis of credit application by credit analysts.

Despite the limitations of the MDA, there is no doubt that credit risk models based on this statistical technique will continue to be one of the major tools in predicting credit risk in consumer lending. Altman (2002) provides analysis suggesting that his Z-score model based on the MDA is competitive with probit KMV's EDF model that is more mathematically sophisticated.

Even though the new model does not have 100% explanatory power the results obtained give support to the MDA. The results in this thesis work showed that the MDA should be applied to the evaluation of credit applications. We can conclude that the existing FcA's credit scoring model can be improved utilizing the MDA. But it is also important to remember that it's necessary to keep the new credit scoring model updated by continuously monitoring its performance to ensure the quality of credit decisions.

It is envisaged that FcA can use the new credit scoring model to gain important strategic advantage and a competitive edge over its rivals.

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APPENDIX I : Table all-definitions of the variables selected for the MDA

N	*Name of the variable*	*Description*
1	Years in business (YrsB)	Years in business
2	Hard Currency Income (HcInc)	% of hard currency in Company Income
3	Business Type (BusType)	Number of business areas
4	Company's area of business (CompBus)	See Appendix II
5	% of Sales Covered by Long Term Contracts (SalCvLnTrmCtr)	% of sales covered by long term contracts
6	Current ratio (CurRt) =	Total current assets/Total current liabilities
7	Solvency ratio (SolvRt) =	(Total assets – Total liabilities)/Total assets
8	Gross Profit Margin (GpSales) =	Gross Profit / Sales
9	Growth Ratio of Fleet by number of units in 3-years period (G3N) =	(Final number of units/Initial number of units)^(1/3)-1
10	Growth Ratio of Fleet by number of units in 5-years period (G5N) =	(Final number of units/Initial number of units)^(1/5)-1
11	Repaid of Existing Financing (RpExFin)	% of repaid of Existing Financing
12	Payment Record (PayRec)	See Appendix II

Table 24: Variables selected for the MDA

APPENDIX II : List all values of CompBus and PayRec

A. List all values of the variable "Company's area of business (CompBus)"

Company's area of business

1. Agriculture Materials & Products
2. Building and Construction
3. Consumer goods (Retail/Wholesae)
4. Exchangeable Load Carrier
5. Forest & Paper
6. General Cargo
7. Chemicals goods
8. Ore & Coal
9. Grocery & Food, Daily commodities
10. Waste & Recycling
11. Other

Unique numeric equivalents assigned by *STATISTICA* to CompBus during the new credit scoring model building for Romania. These numeric equivalents are required to use in the Z-score calculation for each particular company.

Company's area of business	Numeric equivalents
11	1
1	2
6	3
2	4
3	5
7	6
5	7
10	8
9	9
8	10

Table 25: Numeric equivalents assigned by *STATISTICA* to CompBus

APPENDIX II (Continuation I)

B. List all values of the variable "Payment Record (PayRec)"

Payment Record:

A(1): Excellent, always pays on time
B(2): Good, pays normally on time, occasional delays
C(3): Slow, pays normally without major problems although seldom on time
D(4): Poor, frequent overdues more than 30 days
E(5): Very poor, experience previous repossessions
X(0): Payment record not available

The following numeric equivalents are required to use in the Z-score calculation for each particular company:

Payment Record	Numeric equivalents
0	1
1	2
2	3
4	4
3	5

Table 26: Numeric equivalents assigned by *STATISTICA* to PayRec

APPENDIX III : Table of the sample sizes by countries

N		Bad	Good	Total
1	Bosnia	23	18	41
2	Bulgaria	7	30	37
3	Belarus	7	15	22
4	Serbia	10	41	51
5	Croatia	28	57	85
6	Indonesia	5	15	20
7	Lithuania	3	3	6
8	Latvia	15	27	42
9	Macedonia	1	20	21
10	Romania	106	238	344
11	Russia	12	15	27
12	Turkey	7	94	101
13	Ukraine	27	38	65
	Overall	251	611	862

Table 27: Table of the sample sizes by countries 2001 – 2005

APPENDIX IV : Table of 201 “good” and 62 “bad” Romanian companies

Table 28: Table of 201 “good” and 62 “bad” Romanian companies (2002-2005) for the new credit scoring model building

N	Comp Bus	YrsB	HcInc	Bus Type	SalCvLn TrmCtr	Gp Sales	CurRt	SolvRt	RpExFin	PayRec	G5num	G3num	Status	FcA score	Z
RO1	1	10	1	1	0	1	0.15	-0.37	0	1	126.79%	291.49%	Good	C	0.76275
RO2	2	12	0	1	0.16	0.29	2.04	0.52	0.66	2	126.79%	44.22%	Good	B	1.825679
RO3	3	10	0.75	1	0.4	0.62	1.18	0.04	0.16	2	46.14%	41.90%	Good	B	-0.55994
RO4	3	9	0.98	1	0	0.83	1.41	0.12	0.38	3	39.06%	33.21%	Good	B	-0.52984
RO5	3	11	0.8	2	0.8	0.67	3.03	0.12	0.31	3	398.55%	45.01%	Bad	B	-1.63165
RO6	3	12	0	2	0	0.63	11.97	0.97	0	1	140.22%	10.06%	Good	C	1.615947
RO7	3	7	0.98	1	0.57	0.75	0.98	0.16	0.37	2	179.31%	104.08%	Bad	B	-0.21024
RO8	1	12	0	1	0.14	0.68	4.19	0.88	0.84	2	145.95%	31.04%	Good	C	2.924374
RO9	3	5	0.9	2	0.6	0.73	2.08	0.32	0.36	4	34.34%	18.56%	Bad	C	-2.42754
RO10	4	13	0	2	0.81	0.74	1.59	0.51	0.39	2	4.94%	6.78%	Good	B	0.462548
RO11	3	12	0.95	3	0.47	0.81	1.32	-0.05	0.55	5	156.02%	6.92%	Bad	B	-2.79213
RO12	5	8	0	1	0	0.08	0.83	0	0	2	14.87%	25.99%	Good	C	-0.51666
RO13	6	11	0	2	0.9	0.07	0.55	0.42	0.37	4	47.58%	91.29%	Bad	C	-2.76136
RO14	3	12	0.9	2	0.87	0.68	1.09	0.18	0.47	4	22.10%	8.20%	Bad	B	-2.48179
RO15	3	11	0.8	2	0.72	0.61	1.47	-0.04	0.4	4	39.77%	33.89%	Bad	C	-2.47926
RO16	3	10	0.5	2	0.3	0.45	0.94	0.1	0.33	2	74.11%	47.36%	Good	B	0.172511
RO17	1	10	0.7	3	0.35	0.66	2.26	0.33	0.74	2	37.97%	18.56%	Good	B	1.59343
RO18	3	15	0.66	1	0	0.68	0.77	0.34	0	2	8.45%	14.47%	Good	B	-0.45377
RO19	3	11	1	2	0	0.56	1.43	0.18	0.69	2	133.89%	32.64%	Good	B	1.295375
RO20	3	10	0.75	2	0.5	0.56	1.17	0.05	0.46	2	164.72%	29.40%	Good	B	0.209099
RO21	6	10	0	1	0	0.04	1.27	0.22	0	1	14.87%	25.99%	Good	D	0.508552
RO22	3	7	0.2	2	0.85	0.75	1.38	0.03	0.45	2	156.02%	30.06%	Good	B	0.483385
RO23	3	8	0	2	0.9	0.54	0.89	0.13	0.3	4	17.61%	8.74%	Bad	C	-2.31032
RO24	3	6	0.05	2	0.75	0.5	1.2	0.04	0.31	5	78.26%	81.71%	Bad	C	-3.29824

APPENDIX IV : Table of 201 “good” and 62 “bad” Romanian companies (Continuation I)															
N	**Comp Bus**	**YrsB**	**HcInc**	**Bus Type**	**SalCvLn TrmCtr**	**Gp Sales**	**CurRt**	**SolvRt**	**RpExFin**	**PayRec**	**G5num**	**G3num**	**Status**	**FcA score**	**Z**
RO25	3	11	0	1	0.9	0.33	0.88	0.19	0.51	2	14.87%	10.06%	Good	B	0.39677
RO26	1	10	0.35	2	0.7	0.39	1.72	0.34	0.36	2	20.11%	7.72%	Good	B	0.048298
RO27	3	8	0.9	1	0.9	0.65	3.94	0.26	0.29	3	47.58%	40.95%	Bad	B	-1.90279
RO28	3	8	0.95	1	0.95	0.75	1.37	0.21	0.31	3	33.03%	31.48%	Good	B	-1.9342
RO29	3	8	0.98	1	0	0.68	1.17	0.02	0.41	5	133.89%	91.29%	Good	C	-2.82788
RO30	3	10	1	1	0.84	0.72	0.84	0.09	0.62	4	35.10%	4.00%	Bad	C	-2.04111
RO31	3	10	0.9	1	0.7	0.57	0.84	0.2	0.71	5	22.31%	21.49%	Bad	B	-2.75535
RO32	7	7	0.7	3	0.65	0.4	0.81	0.2	0.39	5	140.22%	25.99%	Bad	C	-3.95982
RO33	3	13	1	1	1	0.73	1.08	0.05	0.56	2	145.95%	8.74%	Good	B	-0.16109
RO34	4	11	0	1	0.7	-0.1	0.83	0.25	0.66	3	37.97%	18.56%	Bad	C	-0.4928
RO35	3	6	0	1	1	0.57	1.18	0.14	0.23	2	97.44%	44.22%	Good	C	-0.36962
RO36	5	11	0	3	0.75	0.18	0.75	0.15	0.45	4	14.87%	25.99%	Bad	C	-2.14722
RO37	6	10	0	2	0.2	0.06	0.73	0.27	0.61	2	58.49%	0.00%	Good	C	1.072226
RO38	4	12	0	1	0	0.64	0.81	0.31	0.7	2	133.89%	20.51%	Good	B	2.289938
RO39	3	12	1	1	0	0.61	1.6	-0.07	0.54	5	109.13%	58.74%	Bad	B	-2.49038
RO40	5	11	0	1	0.12	0.13	2.09	0.65	0.27	2	97.44%	210.72%	Good	B	0.277209
RO41	3	3	0.1	2	0.85	0.58	1.02	0.1	0.3	3	118.67%	35.72%	Bad	C	-1.18486
RO42	3	10	0.95	1	0	0.71	0.94	0.19	0.37	2	28.47%	20.51%	Good	B	0.461996
RO43	3	3	0.95	1	0.63	0.62	2.06	-0.02	0.35	4	201.71%	529.96%	Good	C	-2.64831
RO44	4	4	1	0	0	0.64	0.36	0.18	0.43	5	133.89%	312.13%	Bad	C	-2.91995
RO45	5	8	0	3	0.56	0.3	0.73	0.12	0	5	82.06%	171.44%	Bad	C	-4.34752
RO46	3	8	0.75	2	0.75	0.67	1.09	0.1	0.34	5	53.42%	16.81%	Bad	B	-3.73232
RO47	4	11	0	1	0.93	0.47	1.94	0.68	0	2	10.76%	18.56%	Bad	B	-1.15407
RO48	3	4	0.95	1	0	0.69	1.26	0.03	0.38	3	160.52%	33.89%	Good	B	-0.6372
RO49	3	2	0	1	0.85	0.66	5.09	0.15	0.24	3	97.44%	44.22%	Bad	C	-1.07386
RO50	1	3	0.1	1	0	0.93	0.94	0.15	0.58	2	109.13%	10.06%	Good	C	2.309087
RO51	3	11	0.95	2	0.85	0.59	2.26	0.04	0.36	2	26.86%	32.00%	Good	A	-0.65841
RO52	4	4	0	2	0	0.13	1.04	0.25	0.37	3	126.79%	44.22%	Good	C	-0.34599

APPENDIX IV : Table of 201 “good” and 62 “bad” Romanian companies (Continuation II)															
N	**Comp Bus**	**YrsB**	**HcInc**	**Bus Type**	**SalCvLn TrmCtr**	**Gp Sales**	**CurRt**	**SolvRt**	**RpExFin**	**PayRec**	**G5num**	**G3num**	**Status**	**FcA score**	**Z**
RO53	6	4	0	2	0.49	0.09	0.67	-0.14	0.79	4	145.95%	21.64%	Bad	C	-0.92451
RO54	6	12	0.2	2	0.24	0.11	0.93	0.33	0.37	2	43.10%	44.22%	Good	B	0.125431
RO55	4	10	0	1	0.54	0.55	1.61	0.11	0.48	2	14.87%	16.96%	Good	B	0.890565
RO56	3	10	0.95	1	0	0.69	2.93	0.01	0.48	2	140.22%	16.96%	Good	B	0.851786
RO57	5	11	0.02	2	0.5	0.17	1.15	0.04	0.23	5	43.10%	81.71%	Bad	C	-3.67997
RO58	8	4	0	1	0.9	-0.18	0.86	0.02	0.19	5	140.22%	16.96%	Bad	C	-4.82184
RO59	1	6	0.7	2	0	0.94	0.73	-0.07	0	2	97.44%	14.47%	Good	B	-0.10378
RO60	3	10	0.96	2	0.9	0.57	4.44	0.1	0.27	2	41.47%	34.42%	Good	B	-0.96269
RO61	6	10	0	1	0.45	0.07	1.62	0.26	0.58	2	97.44%	44.22%	Good	C	0.715759
RO62	3	11	0.9	1	0.6	0.65	1.69	0.23	0.2	1	188.54%	115.44%	Bad	C	0.345974
RO63	3	10	0.96	2	0.77	0.43	0.8	0.04	0.45	3	118.67%	71.00%	Good	B	-1.60705
RO64	3	0	0.95	1	0	0	0	0	0	1	212.91%	569.43%	Bad	C	-0.2815
RO65	3	13	0.2	2	0.79	0.59	1.12	0.26	0	1	12.13%	5.73%	Good	B	0.099565
RO66	1	4	0	2	0.88	0.22	0.62	-0.03	0.72	3	145.95%	14.47%	Good	C	-0.00597
RO67	3	9	1	1	0.95	0.7	10.27	0.1	0.24	3	33.56%	61.98%	Good	B	-1.97392
RO68	3	8	0.5	2	0.55	0.41	3.09	0.55	0.64	2	97.44%	44.22%	Good	C	0.879745
RO69	4	8	0	2	1	0.13	0.7	0.17	0.63	2	118.67%	71.00%	Good	B	0.38853
RO70	5	7	0	1	0.4	0.28	0.8	0.17	0.15	1	82.06%	171.44%	Bad	C	0.787211
RO71	3	8	0.08	3	0.72	0.93	0.69	0.13	0	1	83.84%	51.83%	Bad	C	0.608211
RO72	3	2	0.99	1	0.95	0.73	1.57	0.02	0.27	2	145.95%	348.14%	Bad	B	-0.99028
RO73	3	7	0	3	1	0.08	1.12	0.16	0.17	3	6.96%	11.87%	Bad	C	-2.1447
RO74	5	3	1	1	0.45	0.88	0.25	0.11	0	1	58.49%	115.44%	Good	C	-0.17588
RO75	6	4	0	2	0	0.04	0.45	0.03	0	1	97.44%	14.47%	Good	D	0.483026
RO76	5	12	0.01	2	0.53	0.33	2.01	0.68	0.36	2	14.87%	25.99%	Good	B	0.246841
RO77	3	2	0.34	2	0	0.25	1.1	0.09	0.36	5	140.22%	330.89%	Bad	C	-2.7665
RO78	6	2	0.15	2	0.3	0.04	1.09	0.34	0	1	47.58%	91.29%	Bad	C	-0.00283
RO79	3	8	0.4	2	0.3	0.64	0.68	-0.09	0.31	2	20.11%	18.56%	Good	C	0.378574
RO80	5	1	0	2	0.57	0.22	0.96	0.11	0	1	82.06%	171.44%	Good	C	0.059445

APPENDIX IV : Table of 201 “good” and 62 “bad” Romanian companies (Continuation III)															
N	**Comp Bus**	**YrsB**	**HcInc**	**Bus Type**	**SalCvLn TrmCtr**	**Gp Sales**	**CurRt**	**SolvRt**	**RpExFin**	**PayRec**	**G5num**	**G3num**	**Status**	**FcA score**	**Z**
RO81	9	2	0	1	0	0.08	1.04	0.07	0	1	58.49%	115.44%	Good	D	0.32145
RO82	7	2	0.7	2	0.6	0.18	1.97	0.91	0	1	172.41%	431.33%	Bad	C	-0.81346
RO83	4	6	0	2	0.3	0.48	2.11	0.62	0.13	1	4.03%	6.80%	Good	C	1.145819
RO84	4	8	0	2	0.55	0.15	2.68	0.7	0	1	20.11%	35.72%	Good	C	0.143433
RO85	5	30	0	2	0.68	0.2	1.74	0.67	0	1	4.56%	7.72%	Good	C	-0.06672
RO86	4	9	0	2	1	0.53	2.27	0.74	0	1	67.03%	17.57%	Good	C	-0.04912
RO87	3	3	0.05	1	0.7	0.73	1.81	0.19	0.33	2	140.22%	330.89%	Good	B	0.426018
RO88	3	11	0	1	0.25	0.59	2.54	0.24	0	2	97.44%	44.22%	Good	C	-0.13621
RO89	3	10	0.65	2	0.9	0.45	0.37	-0.02	0	1	145.95%	44.22%	Bad	C	-0.62819
RO90	3	11	0.9	2	0	0.62	2.12	0.37	0.45	2	97.44%	44.22%	Good	B	0.714945
RO91	7	12	0.3	2	0.44	0.16	0.71	0.07	0	1	109.13%	242.00%	Bad	C	-0.28839
RO92	6	10	0.03	2	0.47	0.33	1.13	0.51	0	1	8.45%	14.47%	Good	C	0.186192
RO93	7	10	0.07	2	0	0.39	1.08	0.49	0	1	82.06%	171.44%	Good	C	0.691718
RO94	1	7	0	1	0	0.13	1.21	0.3	0	1	58.49%	115.44%	Good	C	0.954393
RO95	4	9	0	2	0.65	0.38	1.05	0.33	0.15	1	182.52%	21.64%	Bad	C	0.662846
RO96	7	11	0	1	0.6	0.48	1.86	0.46	0	1	58.49%	115.44%	Bad	C	0.151748
RO97	3	7	0	1	0.2	0.39	0.33	-0.18	0.47	2	24.57%	44.22%	Good	C	1.147518
RO98	2	3	0	2	0.36	0.17	0.94	-0.04	0	1	58.49%	115.44%	Good	C	0.480533
RO99	8	5	0.95	1	0.8	0.31	0.94	0.02	0.24	2	23.16%	41.50%	Good	B	-1.64488
RO100	2	11	0	1	0	0.39	1.28	0.35	0	1	58.49%	115.44%	Good	C	1.129304
RO101	3	0	0.7	2	0.8	0	0	0	0	1	133.89%	312.13%	Bad	C	-0.9936
RO102	3	10	0	1	0.45	0.52	0.81	0.05	0.58	2	17.08%	30.06%	Good	C	1.332767
RO103	3	9	0.7	1	0	0.91	2.66	-0.01	0.28	5	31.95%	33.89%	Bad	C	-2.70002
RO104	7	12	0	2	0.9	0.41	1.41	0.26	0.58	2	109.13%	242.00%	Good	B	0.419137
RO105	9	0	0	1	0.8	0	0	0	0	1	58.49%	115.44%	Good	C	-0.74336
RO106	3	0	0	1	0	0	0	0	0	1	58.49%	115.44%	Bad	D	0.64896
RO107	9	9	0	2	0.12	0.05	1.09	0.3	0.3	2	10.76%	18.56%	Good	C	-0.02508
RO108	6	8	0	1	0	0.07	2.09	0.55	0	1	82.06%	25.99%	Good	D	0.562382

APPENDIX IV : Table of 201 “good” and 62 “bad” Romanian companies (Continuation IV)															
N	**Comp Bus**	**YrsB**	**HcInc**	**Bus Type**	**SalCvLn TrmCtr**	**Gp Sales**	**CurRt**	**SolvRt**	**RpExFin**	**PayRec**	**G5num**	**G3num**	**Status**	**FcA score**	**N**
RO109	7	12	0.3	1	0.6	0.19	2.27	0.5	0.1	1	22.22%	9.26%	Bad	C	-0.08772
RO110	4	11	0	1	0.89	0.5	1.58	0.5	0	1	3.71%	6.27%	Good	C	0.032682
RO111	3	3	1	1	0	0.68	0.62	0.01	0.49	5	109.13%	58.74%	Bad	C	-2.61244
RO112	4	9	0	2	0.4	0.58	0.77	0.01	0	1	14.87%	25.99%	Good	C	0.66908
RO113	5	10	0	3	0.75	0.19	1.35	0.69	0	1	24.57%	44.22%	Good	C	-0.17203
RO114	3	4	0	1	1	0.38	0.49	0.03	0	1	82.06%	171.44%	Good	C	-0.17348
RO115	7	1	0.3	1	0.38	0.19	1.07	0.06	0	1	58.49%	115.44%	Bad	C	-0.1771
RO116	5	9	0	1	0	0.04	0.91	0.21	0.21	3	16.72%	29.40%	Bad	C	-1.01181
RO117	3	11	0.9	1	0.65	0.61	1.12	0.36	0	1	8.10%	6.04%	Bad	C	-0.3997
RO118	3	4	0.5	1	0.9	0.98	0.69	-0.63	0	1	47.58%	91.29%	Bad	C	0.028706
RO119	3	4	0.95	2	0	0.53	6.52	-0.02	0.12	2	62.98%	125.72%	Good	B	-0.32209
RO120	4	9	0	1	0	0.34	1.37	0.47	0.14	2	4.94%	8.37%	Good	C	0.259272
RO121	3	9	0.95	1	0.95	0.8	2.71	0.23	0.41	2	29.67%	30.06%	Good	B	-0.40831
RO122	8	11	0.8	1	0.8	0.29	0.99	0.38	0	1	5.15%	8.74%	Good	C	-1.14993
RO123	9	4	0	1	0	0.13	0.93	-0.07	0	1	194.09%	8.97%	Good	D	0.365197
RO124	4	10	0	2	0.5	0.65	0.94	0.46	0	1	1.92%	3.23%	Good	D	0.620792
RO125	5	7	0	1	0	0.06	0.79	-0.12	0	1	14.87%	25.99%	Bad	D	0.585039
RO126	4	10	0	2	0	0.04	0.97	0.26	0.63	2	3.71%	6.27%	Good	B	1.508227
RO127	6	10	0	1	0	0.52	1.12	0.61	0	1	14.87%	25.99%	Bad	C	0.956729
RO128	3	6	0.8	1	0	0.45	2.2	0.41	0.4	2	24.57%	44.22%	Good	B	0.4974
RO129	2	8	0.4	1	0.6	0.14	1.08	0.08	0	1	58.49%	115.44%	Bad	C	-0.22227
RO130	3	2	0	1	0.51	0.51	0.94	0.31	0.51	2	118.67%	268.40%	Good	C	1.034974
RO131	3	10	0.9	2	0	0.58	1.19	0.55	0	1	82.06%	25.99%	Good	C	0.351707
RO132	3	11	0.4	2	0.85	0.62	0.82	0.12	0	1	2.90%	2.33%	Bad	C	-0.14913
RO133	3	4	0.7	1	0	0.98	0.72	0.18	0	1	82.06%	171.44%	Good	C	0.910334
RO134	3	10	0.1	2	0.7	0.71	0.56	0.2	0	1	43.10%	44.22%	Good	C	0.400945
RO135	8	12	0	1	0.73	-0.05	0.27	-1.64	0.53	2	97.44%	210.72%	Good	C	-0.07713
RO136	3	10	0.2	2	0.45	0.29	0.52	0.1	0	1	20.11%	18.56%	Good	C	0.204566

APPENDIX IV : Table of 201 “good” and 62 “bad” Romanian companies (Continuation V)															
N	Comp Bus	YrsB	HcInc	Bus Type	SalCvLn TrmCtr	Gp Sales	CurRt	SolvRt	RpExFin	PayRec	G5num	G3num	Status	FcA score	N
RO137	3	10	0.85	1	0.4	0.37	1.41	0.36	0	1	97.44%	44.22%	Good	C	-0.26907
RO138	1	6	0	2	0	0.12	1.09	0.1	0	1	82.06%	171.44%	Good	C	0.941223
RO139	9	8	0	2	0	0.12	2.44	0.77	0	1	31.95%	25.99%	Good	D	0.402769
RO140	4	8	0	2	0.25	0.76	0.8	0.17	0	1	17.08%	16.26%	Bad	C	1.019261
RO141	5	8	0	1	0	0.04	1.11	0.31	0	1	133.89%	20.51%	Bad	C	0.576132
RO142	3	11	0	1	0.8	0.51	1.17	0.46	0	1	1.30%	2.17%	Good	C	0.209571
RO143	3	6	0.48	3	0.9	0.23	1.07	0.07	0.15	1	140.22%	330.89%	Bad	C	-0.17466
RO144	6	9	0	2	0.58	0.09	1.27	0.48	0	1	82.06%	25.99%	Good	C	-0.13807
RO145	3	2	0	1	0.6	0.27	0.68	0.62	0	1	109.13%	242.00%	Bad	C	0.207135
RO146	1	10	0	1	0	0.09	0.94	0.08	0	1	58.49%	115.44%	Good	D	0.908251
RO147	7	4	0	3	0	0.49	1.8	0.58	0.42	2	109.13%	242.00%	Good	C	1.079027
RO148	5	9	0.1	1	0	0.1	1.06	0.35	0	1	97.44%	210.72%	Good	C	0.533238
RO149	6	125	0	1	0	0.39	2.77	0.74	0.32	2	11.38%	19.68%	Good	B	0.772249
RO150	5	3	0.1	1	0.43	0.3	2.16	0.53	0	1	58.49%	115.44%	Good	C	0.241801
RO151	3	2	0	2	0	0.4	1.91	0.46	0.22	2	140.22%	330.89%	Good	B	0.657401
RO152	1	13	0.05	2	0	0.11	1.31	0.16	0.23	2	37.97%	25.99%	Good	B	0.492795
RO153	3	12	0.95	2	0.5	0.64	0.8	0.08	0	1	18.47%	32.64%	Bad	C	-0.2509
RO154	4	13	0	2	0.3	0.52	0.86	0.48	0.39	2	14.87%	25.99%	Good	B	0.84233
RO155	6	31	0.27	2	0.74	0.28	1.38	0.66	0.59	2	21.67%	38.67%	Good	B	0.326583
RO156	3	8	0	2	0	0.17	1.78	0.48	0	1	4.56%	7.72%	Good	C	0.864755
RO157	3	10	0	2	0.2	0.77	0.79	0.1	0	1	24.57%	14.47%	Good	C	1.160754
RO158	1	4	1	1	1	0.66	0.78	0.17	0.24	2	118.67%	268.40%	Good	B	-1.09996
RO159	6	9	0	1	1	0.04	1.7	0.4	0	1	58.49%	115.44%	Bad	C	-0.67426
RO160	3	12	0.75	2	1	0.66	0.88	0.21	0.22	2	140.22%	58.74%	Good	B	-1.06014
RO161	1	9	0	1	0.48	0.24	0.93	0.05	0.45	1	31.95%	58.74%	Good	C	1.893638
RO162	7	7	0	2	0	0.12	-0.78	0.86	0	1	8.45%	14.47%	Good	C	0.44765
RO163	4	9	0.01	2	0.52	0.45	5.05	0.77	0	1	97.44%	210.72%	Good	C	0.526332
RO164	2	2	0.98	2	0.23	0.05	0.54	-0.19	0.36	2	109.13%	242.00%	Good	B	-0.43659

APPENDIX IV : Table of 201 “good” and 62 “bad” Romanian companies (Continuation VI)															
N	**Comp Bus**	**YrsB**	**HcInc**	**Bus Type**	**SalCvLn TrmCtr**	**Gp Sales**	**CurRt**	**SolvRt**	**RpExFin**	**PayRec**	**G5num**	**G3num**	**Status**	**FcA score**	**N**
RO165	3	6	0	2	0	0.51	0.82	0.07	0	1	164.72%	86.63%	Good	C	1.155636
RO166	2	13	0	2	0.16	0.19	1.33	0.21	0	1	8.45%	14.47%	Good	C	0.750783
RO167	8	9	0	1	0	0.26	0.81	0.4	0	1	3.71%	6.27%	Good	C	0.556667
RO168	3	11	0.8	1	0	0.6	1.35	0.12	0	1	21.67%	25.99%	Bad	C	0.4735
RO169	3	2	0	2	0	0.6	0.98	0.43	0	1	82.06%	171.44%	Good	C	1.245525
RO170	5	10	0	2	0	0.33	0.55	-0.59	0	1	97.44%	14.47%	Good	C	0.832293
RO171	3	8	0	1	1	0.48	1.74	0.5	0	1	109.13%	242.00%	Good	C	-0.04023
RO172	3	11	0	2	0.9	0.3	0.75	-0.02	0	1	8.45%	14.47%	Good	C	-0.12124
RO173	3	12	0	2	0.8	0.47	2.77	0.36	0	2	140.22%	330.89%	Good	B	-0.90017
RO174	3	11	0.98	1	0.85	0.85	1.75	0.34	0.23	2	185.60%	85.02%	Good	B	-0.86813
RO175	3	8	1	1	0	0.76	1.92	0.35	0	1	40.63%	76.52%	Good	C	0.446306
RO176	7	9	0.6	1	0.4	0.4	0.59	0.32	0	1	5.92%	10.06%	Bad	C	-0.31168
RO177	6	6	0	1	0	0.61	1.3	0.3	0	1	4.56%	7.72%	Good	C	1.047241
RO178	3	1	0	1	0.95	0	0.44	0.26	0.19	1	118.67%	268.40%	Good	C	0.12513
RO179	9	4	0	1	0.5	0.19	1.02	0.07	0	1	58.49%	0.00%	Good	D	-0.1735
RO180	5	7	0	1	0	0.07	0.68	0.01	0	1	82.06%	171.44%	Good	D	0.591049
RO181	3	1	0	1	0.3	0	0	0	0	1	58.49%	115.44%	Good	D	0.2901
RO182	3	11	0	1	0	0.32	0.66	-0.74	0	2	97.44%	210.72%	Good	C	-0.15041
RO183	3	9	0.15	2	0.9	0.7	0.59	0.1	0	1	24.57%	31.04%	Good	C	0.104233
RO184	3	0	0	1	0	0	0	0	0	1	58.49%	115.44%	Good	D	0.64896
RO185	4	13	0	1	0.5	0.82	1.06	0.43	0.31	3	37.97%	35.72%	Good	B	-0.48162
RO186	3	13	0.35	2	0	0.12	1.56	0.46	0.31	2	24.57%	8.74%	Good	B	0.323216
RO187	4	3	0	2	0.4	0.45	1.04	0.47	0.3	1	126.79%	44.22%	Good	D	1.500412
RO188	3	12	0.71	1	0.67	0.71	2.19	0.41	0	1	20.64%	10.60%	Good	C	-0.10988
RO189	6	11	0.2	2	0.25	0.31	1.06	0.01	0	1	24.57%	14.47%	Good	C	0.261805
RO190	3	9	0	1	0.65	0.38	0.34	0.21	0	1	109.13%	10.06%	Good	C	0.240518
RO191	3	7	1	1	0	0.68	2	0.59	0	1	8.45%	14.47%	Good	C	0.373322
RO192	5	9	0	2	0	0.22	0.89	0.09	0	1	109.13%	242.00%	Good	C	0.7391

APPENDIX IV : Table of 201 “good” and 62 “bad” Romanian companies (Continuation VII)															
N	**Comp Bus**	**YrsB**	**HcInc**	**Bus Type**	**SalCvLn TrmCtr**	**Gp Sales**	**CurRt**	**SolvRt**	**RpExFin**	**PayRec**	**G5num**	**G3num**	**Status**	**FcA score**	**Z**
RO193	3	0	0	1	0.7	0	0	0	0	1	8.45%	4.00%	Good	D	-0.18838
RO194	3	4	0	1	0.26	0.19	0.94	0.2	0.34	3	168.67%	20.51%	Good	C	-0.62551
RO195	3	7	0	1	0.9	0.53	0.54	0.35	0.22	2	13.40%	23.31%	Good	B	-0.33918
RO196	5	5	0	1	0	0.16	0.52	-0.05	0	1	58.49%	115.44%	Good	D	0.670976
RO197	1	12	0.3	1	0	0.62	0.61	0.29	0	1	5.92%	1.72%	Good	C	1.104167
RO198	3	10	0	1	0.35	0.39	0.77	0.18	0.3	2	14.87%	12.62%	Good	C	0.445961
RO199	3	5	0.95	1	0	0.54	0.47	0.3	0	1	20.11%	18.56%	Good	C	0.242585
RO200	3	0	0	1	0.35	0	0	0	0	1	58.49%	115.44%	Good	D	0.23029
RO201	4	9	0	2	1	0.38	0.38	0.31	0	1	14.87%	25.99%	Bad	C	-0.24947
RO202	3	11	0	1	0.98	0.34	0.87	0.27	0	1	18.47%	32.64%	Good	C	-0.17547
RO203	1	12	0	1	0	0.38	0.71	0.25	0	1	58.49%	115.44%	Good	C	1.174686
RO204	3	12	0.2	2	0.95	0.36	76.55	0.6	0.2	2	133.89%	312.13%	Good	B	1.547892
RO205	1	3	0	1	0.78	0.74	1.04	0.42	0.5	2	182.52%	464.62%	Good	B	1.045702
RO206	3	6	0	1	0.66	0.38	0.27	-0.16	0	1	24.57%	14.47%	Good	C	0.226377
RO207	3	3	0	1	0.7	0.46	0.81	0.34	0.34	2	109.13%	242.00%	Good	C	0.220653
RO208	9	3	0	1	0	0.29	0.26	-0.03	0	1	58.49%	0.00%	Good	D	0.495289
RO209	7	11	0	2	0.5	0.17	0.77	0.07	0	1	14.87%	25.99%	Good	C	-0.05503
RO210	4	13	0	2	0.74	0.58	1.47	0.85	0	1	4.56%	7.72%	Good	C	0.284163
RO211	7	2	0.3	2	0	0.54	5.25	0.38	0	1	97.44%	44.22%	Good	C	0.737776
RO212	3	2	0.8	1	0	0.58	0.3	-0.06	0	1	97.44%	210.72%	Good	C	0.421944
RO213	3	3	0	1	1	0.91	0.62	0.01	0	1	118.67%	7.72%	Good	C	0.330582
RO214	3	3	0	1	0	-0.39	0.67	-0.29	0	1	8.45%	14.47%	Good	D	0.301879
RO215	3	10	0.6	1	0.4	0.21	2.5	0.18	0.3	2	6.96%	11.87%	Good	B	-0.31747
RO216	5	9	0	1	0.85		8.08	0.62	0.19	1	82.06%	171.44%	Good	C	0.337463
RO217	3	6	0.4	1	0	0.36	0.72	0.31	0	1	133.89%	312.13%	Good	C	0.619236
RO218	3	9	0	1	0.6	0.34	0.37	0.15	0	1	82.06%	171.44%	Good	C	0.263524
RO219	2	8	0	2	0	0.19	13.09	0.93	0	1	24.57%	44.22%	Good	C	1.308263
RO220	3	10	0	2	0	0.22	0.55	0.16	0	1	11.84%	11.87%	Good	C	0.873636

APPENDIX IV : Table of 201 "good" and 62 "bad" Romanian companies (Continuation VIII)															
N	**Comp Bus**	**YrsB**	**HcInc**	**Bus Type**	**SalCvLn TrmCtr**	**Gp Sales**	**CurRt**	**SolvRt**	**RpExFin**	**PayRec**	**G5num**	**G3num**	**Status**	**FcA score**	**Z**
RO221	10	52	0.12	1	0.32	0.48	0.73	0.42	0	1	4.28%	7.24%	Good	C	0.116296
RO222	6	12	0	2	0.08	0.09	0.48	0.39	0	1	24.57%	44.22%	Good	D	0.435435
RO223	3	1	0	1	0	0.61	0.3	0.09	0	1	82.06%	171.44%	Good	D	1.233791
RO224	3	1	0.7	2	0	0	0	0	0	1	109.13%	242.00%	Good	D	-0.03664
RO225	4	8	0	1	0.33	0.1	0.95	0.13	0	1	31.95%	58.74%	Good	D	0.305571
RO226	3	2	0	2	0.35	0.15	0.34	0.53	0	1	82.06%	171.44%	Good	D	0.382389
RO227	4	2	0	1	0.37	0.14	1.25	0.21	0	1	58.49%	115.44%	Good	D	0.304799
RO228	4	35	0.25	1	0.54	0.74	1.06	0.47	0	1	11.55%	19.98%	Good	C	0.416731
RO229	3	4	0	1	1	0.93	1.14	0.15	0.15	1	118.67%	18.56%	Good	B	0.838425
RO230	5	10	0	1	0.1	0.13	1.03	0.06	0	1	14.87%	25.99%	Good	D	0.53893
RO231	3	3	0.9	2	0	0.73	1	0	0	1	97.44%	14.47%	Good	C	0.487307
RO232	3	7	0	2	0.35	0.23	0.94	0.03	0.45	2	6.96%	11.87%	Good	C	0.773091
RO233	4	6	0	2	0.96	0.27	0.86	0.14	0	1	5.92%	10.06%	Good	D	-0.29045
RO234	1	11	0	3	0	0.24	0.7	-0.02	0	1	14.87%	25.99%	Good	D	1.042294
RO235	1	6	0	2	0	0.38	0.51	0.2	0.2	2	118.67%	268.40%	Good	C	0.677032
RO236	3	11	0.99	2	1	0.36	0.5	0.04	0	1	160.52%	58.74%	Good	C	-1.16168
RO237	4	10	0	2	0.96	0.58	1.39	0.54	0	1	10.76%	7.72%	Good	C	0.018508
RO238	4	12	0	1	0.35	0.5	1.36	0.45	0	1	3.71%	6.27%	Good	C	0.671782
RO239	3	6	0	2	0	0.49	0.08	-0.06	0	1	97.44%	210.72%	Good	D	1.113731
RO240	3	6	0	1	0.5	0.13	1.1	0.22	0	1	97.44%	44.22%	Good	D	0.207749
RO241	4	1	0	2	0	0	0	0	0	1	82.06%	171.44%	Good	D	0.5764
RO242	7	1	0.4	2	0.6	1	5.42	0.82	0	1	82.06%	171.44%	Good	C	0.361383
RO243	6	10	0	3	0.47	0.05	1.13	0.18	0.23	1	8.45%	14.47%	Good	D	0.676354
RO244	3	4	0	1	0	0.47	0.8	0.09	0.25	2	82.06%	25.99%	Good	C	0.783444
RO245	3	11	0	2	0	0.31	1.14	0.29	0	1	82.06%	171.44%	Good	D	0.976912
RO246	3	0	0	1	0	0	0	0	0	1	58.49%	115.44%	Good	D	0.64896
RO247	8	7	0	2	0	0.01	0	0	0	1	8.45%	14.47%	Good	D	0.295594
RO248	3	11	0	1	0	0.85	3.53	0.61	0.17	1	156.02%	122.40%	Good	C	2.096589

APPENDIX IV : Table of 201 "good" and 62 "bad" Romanian companies (Continuation IX)															
N	**Comp Bus**	**YrsB**	**HcInc**	**Bus Type**	**SalCvLn TrmCtr**	**Gp Sales**	**CurRt**	**SolvRt**	**RpExFin**	**PayRec**	**G5num**	**G3num**	**Status**	**FcA score**	**Z**
RO249	3	1	0	1	0.9	0.45	0.22	0.29	0	1	82.06%	171.44%	Good	D	0.003772
RO250	3	0	0	1	0.85	0	0	0	0	1	58.49%	115.44%	Good	D	-0.36781
RO251	4	2	0	2	0.99	0.56	0.98	0.11	0.25	1	97.44%	210.72%	Good	D	0.738968
RO252	5	10	0	2	0.15	0.05	1.04	0.39	0.15	1	97.44%	210.72%	Good	D	0.876743
RO253	1	9	0	1	0.68	0.16	1.35	0.31	0.19	1	43.10%	25.99%	Good	C	0.772501
RO254	3	1	0	1	0	0	11.45	-0.11	0.32	1	97.44%	210.72%	Good	D	2.01401
RO255	5	7	0	1	0.55	0.08	1.09	0.34	0	1	12.47%	21.64%	Good	D	-0.04466
RO256	3	4	0.67	1	0.87	0.61	1.03	0.37	0	1	82.06%	25.99%	Good	C	-0.4404
RO257	4	2	0	1	0.98	0.91	-0.7	0	0.4	1	168.67%	419.25%	Good	C	1.501618
RO258	3	13	0.5	1	0.9	0.67		0.02	0	1	407.30%	39.04%	Good	B	-0.28524
RO259	1	9	0	1	0	0.68	1.48	0.51	0	1	82.06%	171.44%	Good	C	1.481685
RO260	3	10	0.5	3	0	0.83	0.68	0.18	0.24	2	118.67%	35.72%	Good	B	0.598109
RO261	3	8	0.9	1	0.85	0.73	3.67	0.68	0	1	31.95%	58.74%	Bad	C	-0.44635
RO262	6	6	0.05	1	0.25	0.48	3.75	0.82	0	1	26.58%	29.40%	Good	C	0.652842
RO263	2	10	0.3	2	0	0.28	0.58	0.05	0.14	1	31.95%	30.50%	Bad	C	1.151174

APPENDIX V : Posterior Probabilities for Romanian sample

Table 29: Posterior probabilities for 201 “good” and 62 “bad” Romanian companies

Incorrect classifications are marked with *

	Observed	Good	Bad
1	Good	0.947151	0.052849
2	Good	0.988577	0.011423
3	Good	0.716389	0.283611
4	Good	0.725362	0.274638
5	Bad	0.340513	0.659487
6	Good	0.984479	0.015521
*** 7**	Bad	0.809175	0.190825
8	Good	0.997736	0.002264
9	Bad	0.137050	0.862950
10	Good	0.919925	0.080075
11	Bad	0.084701	0.915299
12	Good	0.729236	0.270764
13	Bad	0.088305	0.911695
14	Bad	0.127819	0.872181
15	Bad	0.128237	0.871763
16	Good	0.882016	0.117984
17	Good	0.983961	0.016039
18	Good	0.747231	0.252769
19	Good	0.975279	0.024721
20	Good	0.887540	0.112460
21	Good	0.924804	0.075196
22	Good	0.922169	0.077831
23	Bad	0.158910	0.841090
24	Bad	0.041893	0.958107
25	Good	0.912446	0.087554
26	Good	0.861480	0.138520
27	Bad	0.256798	0.743202
*** 28**	Good	0.248022	0.751978
*** 29**	Good	0.080685	0.919315
30	Bad	0.219676	0.780324
31	Bad	0.089023	0.910977
32	Bad	0.016145	0.983855
33	Good	0.820166	0.179834
*** 34**	Bad	0.736155	0.263845
35	Good	0.770043	0.229957
36	Bad	0.193921	0.806079
37	Good	0.965925	0.034075
38	Good	0.994225	0.005775
39	Bad	0.126407	0.873593
40	Good	0.897225	0.102775
*** 41**	Bad	0.500219	0.499781

APPENDIX V:Continuation I			
	Observed	Good	Bad
42	Good	0.919864	0.080136
* 43	Good	0.102747	0.897253
44	Bad	0.071131	0.928869
45	Bad	0.009155	0.990845
46	Bad	0.022469	0.977531
* 47	Bad	0.511619	0.488381
48	Good	0.692570	0.307430
* 49	Bad	0.541230	0.458770
50	Good	0.994385	0.005615
51	Good	0.685838	0.314162
52	Good	0.776184	0.223816
* 53	Bad	0.595457	0.404543
54	Good	0.874565	0.125435
55	Good	0.955866	0.044134
56	Good	0.953377	0.046623
57	Bad	0.024237	0.975763
58	Bad	0.004555	0.995445
59	Good	0.832347	0.167653
60	Good	0.581750	0.418250
61	Good	0.943558	0.056442
* 62	Bad	0.906245	0.093755
* 63	Good	0.348746	0.651254
* 64	Bad	0.792341	0.207659
65	Good	0.870298	0.129702
66	Good	0.851607	0.148393
* 67	Good	0.237204	0.762796
68	Good	0.955184	0.044816
69	Good	0.911467	0.088533
* 70	Bad	0.948937	0.051063
* 71	Bad	0.934448	0.065552
* 72	Bad	0.571778	0.428222
73	Bad	0.194502	0.805498
74	Good	0.816913	0.183087
75	Good	0.922132	0.077868
76	Good	0.893002	0.106998
77	Bad	0.087692	0.912308
* 78	Bad	0.852197	0.147803
79	Good	0.910269	0.089731
80	Good	0.863442	0.136558
81	Good	0.903116	0.096884
* 82	Bad	0.634385	0.365615
83	Good	0.969336	0.030664
84	Good	0.877459	0.122541
85	Good	0.839871	0.160129
86	Good	0.843347	0.156653
87	Good	0.915846	0.084154

APPENDIX V: Continuation II			
	Observed	**Good**	**Bad**
88	Good	0.825538	0.174462
* **89**	Bad	0.695406	0.304594
90	Good	0.943492	0.056508
* **91**	Bad	0.790662	0.209338
92	Good	0.884111	0.115889
93	Good	0.941631	0.058369
94	Good	0.959686	0.040314
* **95**	Bad	0.939235	0.060765
* **96**	Bad	0.878780	0.121220
97	Good	0.969410	0.030590
98	Good	0.921865	0.078135
* **99**	Good	0.336133	0.663867
100	Good	0.968600	0.031400
* **101**	Bad	0.570575	0.429425
102	Good	0.976580	0.023420
103	Bad	0.095897	0.904103
104	Good	0.915059	0.084941
105	Good	0.658123	0.341877
* **106**	Bad	0.938050	0.061950
107	Good	0.847999	0.152001
108	Good	0.930165	0.069835
* **109**	Bad	0.835645	0.164355
110	Good	0.858699	0.141301
111	Bad	0.107751	0.892249
112	Good	0.939760	0.060240
113	Good	0.817764	0.182236
114	Good	0.817442	0.182558
* **115**	Bad	0.816643	0.183357
* **116**	Bad	0.563957	0.436043
* **117**	Bad	0.762057	0.237943
* **118**	Bad	0.857982	0.142018
119	Good	0.782268	0.217732
120	Good	0.894749	0.105251
121	Good	0.759736	0.240264
122	Good	0.513157	0.486843
123	Good	0.908640	0.091360
124	Good	0.935580	0.064420
* **125**	Bad	0.932314	0.067686
126	Good	0.981843	0.018157
* **127**	Bad	0.959821	0.040179
128	Good	0.923645	0.076355
* **129**	Bad	0.806406	0.193594
130	Good	0.964060	0.035940
131	Good	0.906964	0.093036
* **132**	Bad	0.822764	0.177236
133	Good	0.957085	0.042915

APPENDIX V:Continuation III			
	Observed	Good	Bad
134	Good	0.912939	0.087061
135	Good	0.837791	0.162209
136	Good	0.886869	0.113131
137	Good	0.795353	0.204647
138	Good	0.958925	0.041075
139	Good	0.913156	0.086844
* 140	Bad	0.963245	0.036755
* 141	Bad	0.931476	0.068524
142	Good	0.887610	0.112390
* 143	Bad	0.817180	0.182820
144	Good	0.825142	0.174858
* 145	Bad	0.887250	0.112750
146	Good	0.956957	0.043043
147	Good	0.966255	0.033745
148	Good	0.927308	0.072692
149	Good	0.947852	0.052148
150	Good	0.892287	0.107713
151	Good	0.938772	0.061228
152	Good	0.923163	0.076837
* 153	Bad	0.799700	0.200300
154	Good	0.952752	0.047248
155	Good	0.903777	0.096223
156	Good	0.954224	0.045776
157	Good	0.969987	0.030013
158	Good	0.531615	0.468385
* 159	Bad	0.680762	0.319238
160	Good	0.546272	0.453728
161	Good	0.989660	0.010340
162	Good	0.918286	0.081714
163	Good	0.926613	0.073387
164	Good	0.752006	0.247994
165	Good	0.969765	0.030235
166	Good	0.946257	0.053743
167	Good	0.929614	0.070386
* 168	Bad	0.921111	0.078889
169	Good	0.973434	0.026566
170	Good	0.952078	0.047922
171	Good	0.845078	0.154922
172	Good	0.828708	0.171292
173	Good	0.604106	0.395894
174	Good	0.615399	0.384601
175	Good	0.918133	0.081867
* 176	Bad	0.784893	0.215107
177	Good	0.964685	0.035315
178	Good	0.874514	0.125486
179	Good	0.817444	0.182556

APPENDIX V:Continuation IV			
	Observed	Good	Bad
180	Good	0.932873	0.067127
181	Good	0.898972	0.101028
182	Good	0.822489	0.177511
183	Good	0.871077	0.128923
184	Good	0.938050	0.061950
185	Good	0.739362	0.260638
186	Good	0.903341	0.096659
187	Good	0.981636	0.018364
188	Good	0.831083	0.168917
189	Good	0.895103	0.104897
190	Good	0.892103	0.107897
191	Good	0.909631	0.090369
192	Good	0.945371	0.054629
193	Good	0.814126	0.185874
194	Good	0.696247	0.303753
195	Good	0.777931	0.222069
196	Good	0.939919	0.060081
197	Good	0.967447	0.032553
198	Good	0.918096	0.081904
199	Good	0.892397	0.107603
200	Good	0.890636	0.109364
* 201	Bad	0.800042	0.199958
202	Good	0.817003	0.182997
203	Good	0.970581	0.029419
204	Good	0.982855	0.017145
205	Good	0.964606	0.035394
206	Good	0.890070	0.109930
207	Good	0.889238	0.110762
208	Good	0.923428	0.076572
209	Good	0.842190	0.157810
210	Good	0.898171	0.101829
211	Good	0.945269	0.054731
212	Good	0.915380	0.084620
213	Good	0.904290	0.095710
214	Good	0.900546	0.099454
215	Good	0.783436	0.216564
216	Good	0.943843	0.056157
217	Good	0.935441	0.064559
218	Good	0.895340	0.104660
219	Good	0.975733	0.024267
220	Good	0.954796	0.045204
221	Good	0.873076	0.126924
222	Good	0.916917	0.083083
223	Good	0.972981	0.027019
224	Good	0.845773	0.154227
225	Good	0.901035	0.098965

APPENDIX V: Continuation V			
	Observed	**Good**	**Bad**
226	Good	0.910729	0.089271
227	Good	0.900933	0.099067
228	Good	0.914780	0.085220
229	Good	0.952490	0.047510
230	Good	0.927874	0.072126
231	Good	0.922585	0.077415
232	Good	0.947913	0.052087
233	Good	0.790151	0.209849
234	Good	0.964433	0.035567
235	Good	0.940422	0.059578
236	Good	0.508801	0.491199
237	Good	0.856132	0.143868
238	Good	0.939986	0.060014
239	Good	0.967891	0.032109
240	Good	0.887341	0.112659
241	Good	0.931502	0.068498
242	Good	0.908167	0.091833
243	Good	0.940367	0.059633
244	Good	0.948666	0.051334
245	Good	0.960958	0.039042
246	Good	0.938050	0.061950
247	Good	0.899712	0.100288
248	Good	0.992324	0.007676
249	Good	0.853422	0.146578
250	Good	0.770518	0.229482
251	Good	0.945361	0.054639
252	Good	0.954994	0.045006
253	Good	0.947869	0.052131
254	Good	0.991333	0.008667
255	Good	0.844218	0.155782
256	Good	0.750954	0.249046
257	Good	0.981668	0.018332
258	Good	0.803997	0.196003
259	Good	0.981128	0.018872
260	Good	0.933525	0.066475
*** 261**	Bad	0.749299	0.250701
262	Good	0.938383	0.061617
*** 263**	Bad	0.969570	0.030430

APPENDIX VI : Exchange rates of Romanian Leu vs. Euro

Year	Rol/Euro	Year	Rol/Euro	Year	Rol/Euro	Year	Rol/Euro
Jan.02	27,773	Jan.03	35,860	Jan.04	40,630	Jan.05	37,516
Feb.02	28,214	Feb.03	35,718	Feb.04	40,014	Feb.05	36,422
Mar.02	28,684	Mar.03	36,168	Mar.04	40,891	Mar.05	36,825
Apr.02	30,152	Apr.03	36,952	Apr.04	40,426	Apr.05	36,211
May.02	31,446	May.03	38,084	May.04	40,796	May.05	36,217
Jun.02	33,296	Jun.03	37,671	Jun.04	40,615	Jun.05	36,050
Jul.02	32,209	Jul.03	37,161	Jul.04	41,088		
Aug.02	32,722	Aug.03	37,240	Aug.04	40,977		
Sep.02	32,508	Sep.03	38,466	Sep.04	41,127		
Oct.02	33,085	Oct.03	39,456	Oct.04	40,870		
Nov.02	33,346	Nov.03	40,193	Nov.04	38,494		
Dec.02	**34,919**	**Dec.03**	**41,117**	**Dec.04**	**39,663**		

Table 30: Exchange rates of the Romanian Leu against the Euro (data are provided by Romanian Central Bank)

APPENDIX VII : Development of the new credit scoring model for Belarus

	Wilks' Lambda	Partial Lambda	F-remove (1,15)	p-level	Toler.	1-Toler. (R-Sqr.)
SolvRt	0.77261	0.771543	4.441556	0.052311	0.751921	0.248079
RpExFin	0.725915	0.821174	3.266526	0.090802	0.521396	0.478604
HcInc	0.722438	0.825125	3.179058	0.094832	0.591862	0.408138
YrsB	0.688951	0.865231	2.336404	0.147192	0.661008	0.338992
PayRec	0.671564	0.887633	1.898877	0.188415	0.76146	0.23854
G5num	0.625263	0.953362	0.73379	0.405135	0.698958	0.301042

Table 31: The MDA and the new credit scoring model generation for Belarus

	Root 1
SolvRt	3.48993
PayRec	0.61059
HcInc	-3.17665
RpExFin	3.80029
YrsB	0.10006
G5num	0.53043
Constant	-1.59833
Eigenval	0.67756
Cum.Prop	1

Table 32: Canonical Analysis for Belarus

	Bad p=.31818	Good p=.68182
SolvRt	9.3119	15.1925
PayRec	0.0628	1.0916
HcInc	11.9509	6.5982
RpExFin	2.0169	8.4205
YrsB	0.2982	0.4668
G5num	2.6777	3.5715

Table 33: Classification functions for Belarus

	Percent Correct	Bad p=.31818	Good p=.68182
Bad	57.14286	4	3
Good	93.33334	1	14
Total	81.81818	5	17

Table 34: Classification matrix for the original sample for Belarus

Belarus	**Size of the sample**		**22**
	Percent of Bad	**Bad**	**Good**
A	0%	0	1
B	28%	2	5
C	72%	5	8
D	0%	0	1

Table 35: Accuracy of the existing FcA credit scoring model for Belarus

APPENDIX VIII : Development of the new credit scoring model for Bosnia

	Wilks' Lambda	Partial Lambda	F-remove (1,34)	p-level	Toler.	1-Toler. (R-Sqr.)
G5num	0.726865	0.808149	8.071424	0.007545	0.794933	0.205067
RpExFin	0.677718	0.866755	5.226765	0.028595	0.6096	0.3904
CurRt	0.667462	0.880074	4.633101	0.038546	0.916142	0.083858
BusType	0.651166	0.902098	3.689912	0.06316	0.722666	0.277334
CompBus	0.631113	0.930762	2.529229	0.121011	0.830101	0.169899
PayRec	0.605299	0.970455	1.035101	0.316149	0.623225	0.376775

Table 36: The MDA and the new credit scoring model generation for Bosnia

	Root 1
G5num	-1.49914
CurRt	0.69581
RpExFin	3.35501
BusType	-0.67054
CompBus	0.14265
PayRec	-0.33950
Constant	0.09114
Eigenval	0.70237
Cum.Prop	1.00000

Table 37: Canonical Analysis for Bosnia

	Bad p=.56098	Good p=.43902
G5num	3.55986	1.09069
CurRt	0.67758	1.82362
RpExFin	-1.26685	4.25902
BusType	2.57954	1.47511
CompBus	0.27753	0.51248
PayRec	0.51154	-0.04763

Table 38: Classification functions for Bosnia

	Percent	**Bad**	**Good**
Bad	78.26087	18	5
Good	77.77778	4	14
Total	78.04878	22	19

Table 39: Classification matrix for the original sample for Bosnia

Bosnia	**Size of the sample**		**41**
	Percent of Bad	Bad	Good
A	0%	0	0
B	0%	0	6
C	48%	11	9
D	52%	12	3

Table 40: Accuracy of the existing FcA credit scoring model for Bosnia

APPENDIX IX : Development of the new credit scoring model for Bulgaria

	Wilks' Lambda	Partial Lambda	F-remove (1,31)	p-level	Toler.	1-Toler. (R-Sqr.)
SolvRt	0.80787	0.6933	13.71365	0.000827	0.715264	0.284736
BusType	0.700185	0.799926	7.75356	0.009056	0.648811	0.351189
RpExFin	0.632003	0.886224	3.97987	0.054902	0.817105	0.182895
G5num	0.623258	0.898659	3.49585	0.070994	0.736062	0.263939
G3num	0.609914	0.91832	2.7573	0.106895	0.737875	0.262125

Table 41: The MDA and the new credit scoring model generation for Bulgaria

	Root 1
SolvRt	-3.59762
BusType	1.00042
RpExFin	2.77781
G5num	-0.94786
G3num	0.59193
Constant	-3.37401
Eigenval	0.78541
Cum.Prop	1

Table 42: Canonical Analysis for Bulgaria

	Bad p=.18919	Good p=.81081
SolvRt	6.99131	14.9088
BusType	3.52057	5.7222
RpExFin	4.69168	10.805
G5num	1.46491	-0.6211
G3num	0.63722	1.9399
Constant	-5.74074	-10.2055

Table 43: Classification functions for Bulgaria

	Percent Correct	Bad p=.18919	Good p=.81081
Bad	71.42857	5	2
Good	93.33334	2	28
Total	89.18919	7	30

Table 44: Classification matrix for the original sample for Bulgaria

Bulgaria	**Size of the sample**		**37**
	Percent of Bad	Bad	Good
A	0%	0	0
B	0%	0	8
C	29%	2	11
D	71%	5	11

Table 45: Accuracy of the existing FcA credit scoring model for Bulgaria

APPENDIX X : Development of the new credit scoring model for Croatia

	Wilks' Lambda	Partial Lambda	F-remove (1,31)	p-level	Toler.	1-Toler. (R-Sqr.)
HcInc	0.906749	0.912622	7.276563	0.008602	0.800469	0.199531
SolvRt	0.853937	0.969063	2.426234	0.123474	0.420093	0.579907
RpExFin	0.847673	0.976225	1.850921	0.177698	0.892856	0.107144
CurRt	0.847528	0.976392	1.837603	0.179247	0.418692	0.581308
G3num	0.846446	0.977640	1.738243	0.191321	0.853298	0.146702
SalCvLnTrmCtr	0.841464	0.983428	1.280690	0.261329	0.950803	0.049197
YrsB	0.838239	0.987211	0.984522	0.324234	0.884280	0.115720

Table 46: the MDA and the new credit scoring model generation for Croatia

	Root 1
HcInc	-2.49029
RpExFin	1.40894
G3num	-0.63526
SalCvLnTrmCtr	0.94544
BusType	-0.35317
SolvRt	2.5961
CurRt	-0.36162
YrsB	-0.02027
Constant	0.92134
Eigenval	0.20843
Cum.Prop	1

Table 47: Canonical Analysis for Croatia

	Bad p=.32941	Good p=.67059
HcInc	8.93465	6.54429
RpExFin	3.52545	4.87785
G3num	1.82891	1.21914
SalCvLnTrmCtr	4.4672	5.37471
BusType	4.93969	4.6007
SolvRt	-0.36187	2.13006
CurRt	0.05383	-0.29328
YrsB	0.04798	0.02852
Constant	-9.33403	-7.58164

Table 48: Classification functions for Croatia

	Percent Correct	Bad p=.32941	Good p=.67059
Bad	42.85714	12	16
Good	89.47369	6	51
Total	74.11765	18	67

Table 49: Classification matrix for the original sample for Croatia

Croatia	**Size of the sample 85**		
	Percent of Bad	Bad	Good
A	0%	0	0
B	25%	7	24
C	54%	15	25
D	21%	6	8

Table 50: Accuracy of the existing FcA credit scoring model for Croatia

One Proportion, Z, Chi-Square Test
H0: Pi = Pi0

Null Proportion (Pi0)	0.1000
Population Proportion (Pi)	0.3300
Alpha (Nominal)	0.0500
Actual Alpha (Exact)	0.0399
Power Goal	0.9000
Actual Power (Normal Approx.)	0.8933
Actual Power (Exact)	0.9041
Required Sample Size (N)	26.0000

Table 51: Sample size calculation for Croatia

Croatia New Credit scoring Model	**Size of the sample** 26		
	Percent of Bad	Bad	Good
Type II Error	50%	13	13

Table 52: Accuracy of additional Power analysis sample classification for Croatia

APPENDIX XI : Development of the new credit scoring model for Indonesia

	Wilks' Lambda	Partial Lambda	F-remove (1,12)	p-level	Toler.	1-Toler. (R-Sqr.)
G5num	0.622437	0.681918	5.597427	0.035667	0.597759	0.402241
RpExFin	0.536628	0.79096	3.171441	0.100244	0.601313	0.398687
BusType	0.504289	0.841682	2.257171	0.158848	0.865424	0.134576
PayRec	0.497381	0.853371	2.061872	0.176577	0.59609	0.40391
SalCvLnTrmCtr	0.493568	0.859964	1.954074	0.187453	0.562464	0.437536
SolvRt	0.485247	0.87471	1.718825	0.214378	0.671237	0.328763
GpSales	0.475791	0.892094	1.451494	0.251512	0.727297	0.272703

Table 53: The MDA and the new credit scoring model generation for Indonesia

	Root 1
BusType	-0.56378
G5num	0.961536
RpExFin	-0.77718
PayRec	0.653751
SalCvLnTrmCtr	-0.65771
SolvRt	-0.56948
GpSales	0.507721
Eigenval	1.355986
Cum.Prop	1

Table 54: Canonical Analysis for Indonesia

	Bad p=.25000	Good p=.75000
BusType	3.9555	1.8665
G5num	-2.9203	-0.18863
RpExFin	6.8905	0.00815
PayRec	-1.5587	0.29741
SalCvLnTrmCtr	11.0853	6.51772
SolvRt	9.499	4.92463
GpSales	0.4366	6.5474
Constant	-13.3515	-6.35606

Table 55: Classification functions for Indonesia

	Percent Correct	Bad p=.25000	Good p=.75000
Bad	100	5	0
Good	93.3333	1	14
Total	95	6	14

Table 56: Classification matrix for the original sample for Indonesia

Indonesia	**Size of the sample**		**20**
	Percent of Bad	Bad	Good
A	0%	0	1
B	20%	1	4
C	80%	4	9
D	0%	0	1

Table 57: Accuracy of the existing FcA credit scoring model for Indonesia

APPENDIX XII : Development of the new credit scoring model for Latvia

	Wilks' Lambda	Partial Lambda	F-remove (1,33)	p-level	Toler.	1-Toler. (R-Sqr.)
PayRec	0.663097	0.497181	33.37425	0.000002	0.417639	0.582361
SolvRt	0.471002	0.699953	14.14605	0.000659	0.524113	0.475887
RpExFin	0.36585	0.901131	3.62065	0.065822	0.561569	0.438431
BusType	0.363432	0.907128	3.37855	0.075067	0.889059	0.110941
G5num	0.348856	0.945029	1.91956	0.175199	0.916602	0.083398
SalCvLnTrmCtr	0.356106	0.925791	2.64521	0.113376	0.705025	0.294976
HcInc	0.356396	0.925036	2.6743	0.111485	0.511324	0.488676
GpSales	0.349419	0.943508	1.97586	0.169173	0.697669	0.302331

Table 58: The MDA and the new credit scoring model generation for Latvia

	Root 1
PayRec	-1.3702
SolvRt	3.01955
RpExFin	1.94143
BusType	-0.59538
G5num	-0.56488
SalCvLnTrmCtr	0.7929
HcInc	1.67752
GpSales	1.9329
Constant	-0.15857
Eigenval	2.03325
Cum.Prop	1

Table 59: Canonical Analysis for Latvia

	Bad p=.35714	Good p=.64286
PayRec	0.9029	-3.0764
SolvRt	9.4148	18.1841
RpExFin	-10.908	-5.2698
BusType	8.4811	6.752
G5num	5.0234	3.3829
SalCvLnTrmCtr	8.5798	10.8825
HcInc	17.3838	22.2556
GpSales	13.2783	18.8917
Constant	-28.9658	-27.6336

Table 60: Classification functions for Latvia

	Percent Correct	Bad p=.35714	Good p=.64286
Bad	80	12	3
Good	96.2963	1	26
Total	90.47619	13	29

Table 61: Classification matrix for the original sample for Latvia

Latvia	**Size of the sample**		**42**
	Percent of Bad	Bad	Good
A	0%	0	0
B	47%	7	12
C	33%	5	12
D	20%	3	3

Table 62: Accuracy of the existing FcA credit scoring model for Latvia

APPENDIX XIII : Development of the new credit scoring model for Russia

	Wilks' Lambda	Partial Lambda	F-remove (1,33)	p-level	Toler.	1-Toler. (R-Sqr.)
G5num	0.811104	0.837176	3.889849	0.062566	0.48862	0.51138
SolvRt	0.76855	0.883529	2.636485	0.120091	0.887722	0.112279
PayRec	0.740498	0.917	1.810248	0.193536	0.470532	0.529468
BusType	0.732978	0.926408	1.588759	0.222011	0.693211	0.306789
SalCvLnTrmCtr	0.714097	0.950901	1.032672	0.321669	0.819393	0.180607
RpExFin	0.71209	0.953583	0.973539	0.335586	0.427871	0.572129

Table 63: The MDA and the new credit scoring model generation for Russia

	Root 1
SalCvLnTrmCtr	1.98857
SolvRt	-1.44532
G5num	-1.11126
BusType	-0.56413
PayRec	-0.70071
RpExFin	2.13032
Constant	1.55979
Eigenval	0.47268
Cum.Prop	1

Table 64: Canonical Analysis for Russia

	Bad p=.44444	Good p=.55556
SalCvLnTrmCtr	24.5756	27.2231
SolvRt	6.7141	4.7899
G5num	6.6665	5.187
BusType	6.0041	5.2531
PayRec	3.7096	2.7767
RpExFin	-17.754	-14.9178
Constant	-23.6961	-21.2978

Table 65: Classification functions for Russia

	Percent Correct	Bad p=.44444	Good p=.55556
Bad	58.33333	7	5
Good	86.66666	2	13
Total	74.07407	9	18

Table 66: Classification matrix for the original sample for Russia

Russia	**Size of the sample**		**27**
	Percent of Bad	Bad	Good
A	0%	0	0
B	25%	3	2
C	50%	6	11
D	25%	3	2

Table 67: Accuracy of the existing FcA credit scoring model for Russia

One Proportion, Z, Chi-Square Test
H0: Pi = Pi0

Null Proportion (Pi0)	0.07
Population Proportion (Pi)	0.52
Alpha (Nominal)	0.05
Actual Alpha (Exact)	0.0578
Power Goal	0.99
Actual Power (Normal Approx.)	0.9877
Actual Power (Exact)	0.9923
Required Sample Size (N)	13

Table 68: Sample size calculation for Russia

Russia New Credit scoring Model	**Size of the sample** 13		
	Percent of Bad	Bad	Good
Type II Error	46%	6	7

Table 69: Accuracy of additional Power analysis sample classification for Russia

APPENDIX XIV : Development of the new credit scoring model for Serbia&Montenegro

	Wilks' Lambda	Partial Lambda	F-remove (1,43)	p-level	Toler.	1-Toler. (R-Sqr.)
BusType	0.793328	0.808219	10.20338	0.002625	0.893965	0.106035
SalCvLnTrmCtr	0.756111	0.848002	7.70742	0.008112	0.712806	0.287194
GpSales	0.672025	0.954106	2.06837	0.157621	0.678459	0.321541
RpExFin	0.661296	0.969586	1.34884	0.251889	0.787817	0.212184
CompBus	0.65961	0.972065	1.23573	0.272473	0.790936	0.209064
YrsB	0.652989	0.98192	0.79173	0.378528	0.801171	0.198829
CurRt	0.649858	0.986652	0.58172	0.449801	0.733685	0.266315

Table 70: The MDA and the new credit scoring model generation for Serbia&Montenegro

	Root 1
BusType	-0.89117
SalCvLnTrmCtr	2.78597
CompBus	0.10145
GpSales	-1.27301
RpExFin	1.35999
YrsB	0.01474
CurRt	0.02438
Constant	-0.61658
Eigenval	0.55962
Cum.Prop	1

Table 71: Canonical Analysis for Serbia&Montenegro

	Bad p=.19608	Good p=.80392
BusType	3.04101	1.39513
SalCvLnTrmCtr	4.07899	9.22431
CompBus	0.44253	0.62991
GpSales	1.45008	-0.90101
RpExFin	-2.03527	0.47645
YrsB	0.07952	0.10674
CurRt	-0.085	-0.03997
Constant	-8.76347	-7.45457

Table 72: Classification functions for Serbia&Montenegro

	Percent Correct	Bad p=.19608	Good p=.80392
Bad	40	4	6
Good	95.12195	2	39
Total	84.31373	6	45

Table 73: Classification matrix for the original sample for Serbia&Montenegro

Serbia	**Size of the sample** **51**		
	Percent of Bad	Bad	Good
A	0%	0	0
B	0%	0	8
C	60%	6	28
D	40%	4	5

Table 74: Accuracy of the existing FcA credit scoring model for Serbia&Montenegro

One Proportion, Z, Chi-Square Test
H0: Pi = Pi0

Null Proportion (Pi0)	0.04
Population Proportion (Pi)	0.19
Alpha (Nominal)	0.05
Actual Alpha (Exact)	0.0457
Power Goal	0.9
Actual Power (Normal Approx.)	0.8951
Actual Power (Exact)	0.9094
Required Sample Size (N)	34

Table 75: Sample size calculation for Serbia&Montenegro

Serbia New Credit scoring Model	**Size of the sample** 34		
	Percent of Bad	Bad	Good
Type II Error	29%	10	24

Table 76: Accuracy of additional Power analysis sample classification for Serbia&Montenegro

APPENDIX XV : Development of the new credit scoring model for Turkey

	Wilks' Lambda	Partial Lambda	F-remove (1,33)	p-level	Toler.	1-Toler. (R-Sqr.)
RpExFin	0.920484	0.909522	9.251533	0.003057	0.842778	0.157222
SalCvLnTrmCtr	0.859074	0.974539	2.429743	0.122449	0.97783	0.02217
HcInc	0.85737	0.976475	2.240552	0.137819	0.931142	0.068858
PayRec	0.852764	0.98175	1.728834	0.191793	0.826823	0.173177
CurRt	0.850442	0.98443	1.470952	0.228267	0.852655	0.147345
SolvRt	0.843928	0.992029	0.747272	0.389566	0.886177	0.113823
G5num	0.842888	0.993252	0.631807	0.428717	0.933947	0.066053

Table 77: The MDA and the new credit scoring model generation for Turkey

	Root 1
RpExFin	4.21351
HcInc	1.49062
SalCvLnTrmCtr	1.10854
PayRec	-0.52455
CurRt	0.01624
SolvRt	-0.46833
G5num	0.47957
Constant	-2.00092
Eigenval	0.19446
Cum.Prop	1

Table 78: Canonical Analysis for Turkey

	Bad p=.06931	Good p=.93069
RpExFin	-2.3479	4.89514
HcInc	7.91643	10.47882
SalCvLnTrmCtr	0.37258	2.27817
PayRec	1.372	0.47029
CurRt	-0.02059	0.00734
SolvRt	1.6062	0.80114
G5num	-0.13138	0.693
Constant	-5.89464	-5.46416

Table 79: Classification functions for Turkey

	Percent Correct	Bad p=.06931	Good p=.93069
Bad	28.57143	2	5
Good	97.87234	2	92
Total	93.06931	4	97

Table 80: Classification matrix for the original sample for Turkey

Turkey	**Size of the sample** **101**		
	Percent of Bad	Bad	Good
A	0%	0	14
B	14%	1	57
C	57%	4	19
D	29%	2	4

Table 81: Accuracy of the existing FcA credit scoring model for Turkey

One Proportion, Z, Chi-Square Test
H0: Pi = Pi0

Null Proportion (Pi0)	0.0200
Population Proportion (Pi)	0.0700
Alpha (Nominal)	0.0500
Actual Alpha (Exact)	0.0715
Power Goal	0.8000
Actual Power (Normal Approx.)	0.7464
Actual Power (Exact)	0.8039
Required Sample Size (N)	78.0000

Table 82: Sample size calculation for Turkey

Turkey New Credit scoring Model	**Size of the sample** 78		
	Percent of Bad	Bad	Good
Type II Error	62%	49	29

Table 83: Accuracy of additional Power analysis sample classification for Turkey

APPENDIX XVI : Development of the new credit scoring model for Ukraine

	Wilks' Lambda	Partial Lambda	F-remove (1,54)	p-level	Toler.	1-Toler. (R-Sqr.)
SolvRt	0.745702	0.933084	3.872603	0.054224	0.755189	0.244811
CompBus	0.724495	0.960397	2.226746	0.141459	0.789154	0.210846
G5num	0.719922	0.966497	1.871864	0.176928	0.600485	0.399515
G3num	0.711593	0.97781	1.225482	0.273195	0.631146	0.368854
SalCvLnTrmCtr	0.706685	0.984601	0.844529	0.362192	0.75727	0.24273
BusType	0.706087	0.985435	0.79811	0.375623	0.773686	0.226314
CurRt	0.70565	0.986045	0.764217	0.385883	0.780269	0.219731
RpExFin	0.700793	0.992879	0.387275	0.536354	0.565909	0.43409
PayRec	0.696851	0.998496	0.081355	0.776561	0.656882	0.343118
YrsB	0.696712	0.998694	0.070604	0.791471	0.833871	0.166129

Table 84: The MDA and the new credit scoring model generation for Ukraine

	Root 1
G5num	-0.49672
SalCvLnTrmCtr	-0.80368
SolvRt	1.64951
CompBus	0.185534
CurRt	-0.05216
G3num	-0.21371
BusType	0.396217
RpExFin	-0.83027
PayRec	-0.0806
YrsB	0.008897
Constant	-0.96655
Eigenval	0.437189
Cum.Prop	1

Table 85: Canonical Analysis for Ukraine

	Bad p=.41538	Good p=.58462
G5num	3.6468	2.9907
SalCvLnTrmCtr	13.8373	12.7756
SolvRt	6.6091	8.788
CompBus	1.7131	1.9582
CurRt	-0.0945	-0.1634
G3num	-0.4706	-0.7529
BusType	5.0271	5.5505
RpExFin	-5.8384	-6.9352
PayRec	0.7926	0.6861
YrsB	0.1009	0.1127
Constant	-17.9056	-18.693

Table 86: Classification functions for Ukraine

	Percent Correct	Bad p=.41538	Good p=.58462
Bad	62.96296	17	10
Good	86.8421	5	33
Total	76.92308	22	43

Table 87: Classification matrix for the original sample for Ukraine

Ukraine	**Size of the sample**		**65**
	Percent of Bad	Bad	Good
A	0%	0	0
B	11%	3	12
C	59%	16	11
D	30%	8	15

Table 88: Accuracy of the existing FcA credit scoring model for Ukraine

One Proportion, Z, Chi-Square Test
H0: Pi = Pi0

Null Proportion (Pi0)	0.13
Population Proportion (Pi)	0.42
Alpha (Nominal)	0.05
Actual Alpha (Exact)	0.0598
Power Goal	0.9
Actual Power (Normal Approx.)	0.8616
Actual Power (Exact)	0.9051
Required Sample Size (N)	17

Table 89: Sample size calculation for Ukraine

Ukraine New Credit scoring Model	**Size of the sample** 17		
	Percent of Bad	Bad	Good
Type II Error	52%	9	8

Table 90: Accuracy of additional Power analysis sample classification for Ukraine

APPENDIX XVII Development of the new credit scoring model for all markets

	Wilks' Lambda	Partial Lambda	F-remove -1,851	p-level	Toler.	1-Toler. (R-Sqr.)
PayRec	0.923628	0.956583	38.62518	0	0.651933	0.348067
RpExFin	0.913976	0.966685	29.32775	0	0.669506	0.330494
G5num	0.895232	0.986925	11.27412	0.000821	0.895444	0.104556
BusType	0.895431	0.986706	11.46586	0.000741	0.959379	0.040621
SalCvLnTrmCtr	0.890166	0.992542	6.39421	0.011629	0.957006	0.042994
SolvRt	0.886996	0.996089	3.34126	0.067913	0.991296	0.008704
CompBus	0.886617	0.996515	2.97595	0.084874	0.988553	0.011447
YrsB	0.885732	0.99751	2.1241	0.145367	0.919675	0.080325
HcInc	0.88574	0.997502	2.1311	0.144706	0.941103	0.058897
CurRt	0.885686	0.997563	2.07916	0.14969	0.975158	0.024843

Table 91: The MDA and the new credit scoring model generation for all markets

	Root 1
PayRec	-0.81516
RpExFin	2.884357
G5num	-0.56461
BusType	-0.4313
SalCvLnTrmCtr	-0.71574
SolvRt	0.087705
CompBus	0.07065
YrsB	0.014126
HcInc	-0.38214
CurRt	0.016978
Constant	1.109083
Eigenval	0.131827
Cum.Prop	1

Table 92: Canonical Analysis for all markets

	Bad p=.29118	**Good p=.70882**
PayRec	0.46393	-0.18678
RpExFin	-0.73985	1.56264
G5num	2.47354	2.02284
BusType	2.63533	2.29104
SalCvLnTrmCtr	3.73556	3.1642
SolvRt	0.08185	0.15186
CompBus	0.87233	0.92872
YrsB	0.11118	0.12246
HcInc	1.95769	1.65265
CurRt	0.01862	0.03217
Constant	-9.31983	-7.41177

Table 93: Classification functions for all markets

	Percent Correct	**Bad p=.29118**	**Good p=.70882**
Bad	25.49801	64	187
Good	93.78069	38	573
Total	73.89791	102	760

Table 94: Classification matrix for the original sample for all markets

Overall	**Size of the sample**		**862**
	Percent of Bad	Bad	Good
A	0%	0	18
B	16%	41	203
C	65%	164	288
D	19%	46	102

Table 95: Accuracy of the existing FcA credit scoring model for all markets

APPENDIX XVIII : Additional sample for Romanian market

Table 96: Additional sample of 37 "good" and 44 "bad" Romanian companies (2001) for the new credit scoring model testing

N	Comp Bus	YrsB	HcInc	Bus Type	SalCvLn TrmCtr	GpSales	CurRt	SolvRt	RpExFin	PayRec	G5num	G3num	Status	FcA rating	Z
RO01	9	7	0	1	0.83	0.05	0.84	0.15	0.22	2	31.95%	58.74%	Good	C	-1.13432
RO02	9	7	0	1	0.6	0.06	1.17	0.18	0	1	58.49%	115.44%	Good	C	-0.41109
RO03	6	2	0	1	1	0.94	1.64	0.35	0	1	58.49%	115.44%	Good	C	0.172957
RO04	6	10	0.26	1	0.42	0.41	3.54	0.84	0	1	4.56%	7.72%	Good	C	0.171231
RO05	3	2	0	1	0.98	0.44	0.66	0.04	0	3	109.13%	242.00%	Good	C	-2.33128
RO06	3	4	0.4	2	0.65	0.83	1.35	0.26	0.21	1	109.13%	58.74%	Good	C	0.966632
RO07	3	10	0.97	1	0.55	0.55	0.61	0.19	0	1	20.11%	18.56%	Good	C	-0.42112
RO08	3	5	0.3	2	0.59	0.33	1.24	0.44	0	1	40.63%	40.10%	Good	C	-0.00069
RO09	3	6	0.97	1	0.95	0.72	0.9	0.45	0.3	5	242.31%	13.67%	Good	A	-4.27186
RO10	3	1	1	2	0.7	0.79	0.71	0	0	1	97.44%	210.72%	Good	C	-0.4004
RO11	3	9	0.9	1	0.8	0.85	0.98	0.11	0	1	31.95%	10.06%	Good	C	-0.35706
RO12	3	1	0	1	1	0.77	0.87	-0.14	0.26	3	185.60%	474.89%	Good	C	-1.21784
RO13	3	4	0.4	2	0.78	0.92	0.34	0.09	0.3	3	109.13%	242.00%	Good	C	-1.09536
RO14	3	2	0.75	1	0.8	0.53	0.52	-0.06	0	1	24.57%	14.47%	Good	C	-0.52637
RO15	3	0	0	1	1	0	0	0	0	1	58.49%	115.44%	Good	D	-0.54724
RO16	3	7	0	1	0.67	0.59	0.6	0.14	0.15	1	55.18%	65.10%	Good	B	0.895594
RO17	5	5	0	1	0.45	0.07	1.21	0.25	0	1	82.06%	25.99%	Good	C	0.069257
RO18	5	5	0	1	0.67	0.1	1.05	0.37	0	1	97.44%	44.22%	Good	C	-0.17058
RO19	5	7	0	1	0.7	0.22	1.04	0.33	0	1	109.13%	242.00%	Good	C	-0.09357
RO20	5	10	0.3	2	0.57	0.11	2.64	0.55	0.25	3	140.22%	330.89%	Good	B	-1.74151
RO21	5	10	0	2	0.4	0.11	0.84	0.44	0	1	8.45%	14.47%	Good	C	0.155287
RO22	5	8	0	1	0.6	0.18	0.84	0.04	0	1	58.49%	115.44%	Good	C	-0.01791
RO23	4	2	0	2	1	0.39	1.08	0.48	0	1	109.13%	242.00%	Good	C	-0.21824
RO24	4	7	0	1	0.85	0.1	1.76	0.39	0	1	145.95%	348.14%	Good	C	-0.29124

APPENDIX XVIII : Additional sample for Romanian market (Continuation I)

N	Comp Bus	YrsB	HcInc	Bus Type	SalCvLn TrmCtr	GpSales	CurRt	SolvRt	RpExFin	PayRec	G5num	G3num	Status	FcA rating	Z
RO25	4	5	0	1	0.56	0.15	0.93	0	0	1	151.19%	364.16%	Good	C	0.076993
RO26	4	7	0	1	0.65	0.1	0.96	0.47	0	1	8.45%	14.47%	Good	C	-0.0769
RO27	4	7	0	1	0.67	0.2	1.15	0.37	0	1	8.45%	14.47%	Good	C	-0.00057
RO28	4	8	0	1	0.58	0.11	0.98	0.16	0	1	58.49%	115.44%	Good	C	0.016889
RO29	4	8	0	1	0.64	0.91	1.42	0.37	0	1	126.79%	291.49%	Good	C	0.713558
RO30	0	10	0	2	0.07	0.31	2.43	0.81	0.32	2	10.76%	18.56%	Good	B	1.037816
RO31	1	7	0	2	0.05	0.47	0.54	0.47	0.25	3	82.06%	171.44%	Good	C	-0.26115
RO32	1	9	0	1	0.28	0.43	3.47	0.81	0.33	2	109.13%	242.00%	Good	B	0.89116
RO33	1	7	0.91	1	0.47	0.88	0.89	0.54	0	1	58.49%	115.44%	Good	C	0.198509
RO34	1	7	0.9	2	0.9	0.15	1.08	0.24	0.28	3	18.47%	32.64%	Good	B	-2.34994
RO35	1	3	0.01	1	0.6	0.17	0.69	0.13	0	1	82.06%	25.99%	Good	C	0.248429
RO36	1	9	0	1	0.35	0.16	1.02	0.22	0	1	82.06%	171.44%	Good	C	0.558111
RO37	1	10	0	1	0	0.52	0.84	0.53	0	1	4.56%	7.72%	Good	C	1.310813
RO38	9	7	0.05	2	0.9	0.06	1.27	0.32	0.2	3	61.54%	122.40%	Bad	C	-2.42905
RO39	9	7	0.17	2	0.85	0.16	0.87	0.03	0.55	5	87.22%	48.67%	Bad	C	-3.54533
RO40	9	1	0.18	2	0.48	0.08	1.14	0.13	0	1	97.44%	210.72%	Bad	C	-0.42591
RO41	9	5	0	1	0.55	0.26	19.36	0.9	0	1	109.13%	25.99%	Bad	C	0.403659
RO42	9	7	0	1	0.45	0.06	1.07	0.44	0.15	1	20.11%	35.72%	Bad	C	0.238011
RO43	9	0	0	2	0.39	0	0	0	0	1	14.87%	25.99%	Bad	D	-0.25292
RO44	10	9	0	2	0.9	0.23	0.83	0.16	0	1	8.45%	14.47%	Bad	C	-0.69271
RO45	10	9	0.1	1	0.45	0.1	0.77	0.3	0	1	31.95%	58.74%	Bad	C	-0.37688
RO46	3	6	0	1	1	0.17	0.3	0.12	0	1	4.56%	7.72%	Bad	D	-0.37752
RO47	3	7	0.85	1	0.6	0.83	1.01	0.14	0	1	188.54%	58.74%	Bad	C	-0.08679
RO48	3	8	0.8	1	0.77	0.2	0.51	0.24	0	1	109.13%	58.74%	Bad	C	-0.8511
RO49	3	4	0.65	1	0.95	0.51	0.44	0.15	0	1	126.79%	44.22%	Bad	C	-0.62921
RO50	3	8	0.85	2	0.96	0.58	1.01	0.31	0.48	3	151.19%	71.00%	Bad	B	-1.48398
RO51	3	10	0	2	0.96	0.57	1.45	0.34	0	1	14.87%	25.99%	Bad	C	0.083502
RO52	3	2	1	1	0.4	0.61	0.53	-0.89	0.05	1	126.79%	291.49%	Bad	C	-0.05936

APPENDIX XVIII : Additional sample for Romanian market (Continuation II)

N	Comp Bus	YrsB	HcInc	Bus Type	SalCvLn TrmCtr	GpSales	CurRt	SolvRt	RpExFin	PayRec	G5num	G3num	Status	FcA rating	Z
RO53	3	7	0	1	0.6	0.24	0.38	0.06	0	1	8.45%	14.47%	Bad	C	0.169493
RO54	3	9	0.5	2	0.8	0.63	0.61	0.12	0.2	1	37.97%	71.00%	Bad	C	0.446017
RO55	3	7	0.9	1	0.33	0.92	0.54	0.24	0.26	3	24.57%	25.99%	Bad	B	-1.16663
RO56	3	7	0.98	1	1	0.9	1.59	0.24	0.25	5	109.13%	242.00%	Bad	B	-4.30776
RO57	3	10	0.954	1	0.6	0.73	0.8	0.35	0	1	10.76%	18.56%	Bad	C	-0.28953
RO58	3	0	0	0	0	0	0	0	0	1	109.13%	242.00%	Bad	C	0.64896
RO59	3	3	0	2	0.85	0.22	0.58	0.8	0.25	5	182.52%	8.74%	Bad	C	-3.84146
RO60	3	9	0.9	2	0.9	0.69	1.68	-0.13	0	1	10.76%	18.56%	Bad	C	-0.60584
RO61	3	9	0.95	2	0.9	0.69	1.65	0.43	0	1	9.46%	16.26%	Bad	C	-0.65575
RO62	3	10	0.95	2	0.9	0.69	2.15	0.35	0	1	18.13%	15.31%	Bad	C	-0.64018
RO63	3	6	0	2	0.9	0.39	0.13	0.06	0	1	20.11%	18.56%	Bad	C	-0.05564
RO64	3	0	0.45	2	0.75	0	0	0	0.13	1	156.02%	379.14%	Bad	C	-0.27919
RO65	3	8	0.95	1	0.9	0.83	1.11	0.02	0.07	1	160.52%	393.24%	Bad	C	-0.31984
RO66	3	8	1	1	0.8	0.61	0.7	-0.54	0	1	14.87%	25.99%	Bad	C	-0.69015
RO67	3	7	0.98	2	1	0.79	0.46	-0.08	0	1	9.86%	16.96%	Bad	C	-0.74745
RO68	3	8	0.05	3	0.5	0.25	0.75	0.01	0.26	5	24.57%	21.64%	Bad	C	-3.40665
RO69	3	10	0.2	3	0.44	0.26	1.06	0.28	0	1	3.96%	4.26%	Bad	C	0.205036
RO70	7	7	0.7	3	0.9	0.52	6.08	0.78	0	1	39.06%	25.99%	Bad	C	-0.72361
RO71	7	6	0	1	0.75	0.41	0.25	-0.65	0.19	1	118.67%	71.00%	Bad	C	0.455022
RO72	5	8	0	1	1	0.05	1.06	0.11	0	1	24.57%	44.22%	Bad	C	-0.61219
RO73	5	10	0.15	2	0.81	0.16	2.7	0.57	0.2	1	37.97%	71.00%	Bad	C	0.253385
RO74	5	9	0.03	2	0.24	0.1	0.61	-0.01	0	1	14.87%	7.72%	Bad	C	0.300701
RO75	4	2	0	2	0.8	0.2	1.7	0.53	0	1	151.19%	364.16%	Bad	C	-0.13895
RO76	4	2	0	1	0.05	0.09	1.16	-0.01	0.38	3	224.53%	611.38%	Bad	C	-0.40828
RO77	4	7	0	2	0.58	0.53	0.99	0.05	0.36	3	97.44%	210.72%	Bad	C	-0.69549
RO78	4	9	0	2	0.5	0.21	1.38	0.43	0.43	3	82.06%	171.44%	Bad	C	-0.66892
RO79	4	9	0	2	0.9	0.13	1.01	0.09	0.17	5	188.54%	484.80%	Bad	C	-4.29751
RO80	1	7	0.01	2	0.71	0.1	0.98	0.01	0	1	82.06%	171.44%	Bad	C	0.059834

APPENDIX XVIII : Additional sample for Romanian market (Continuation III)															
N	**Comp Bus**	**YrsB**	**HcInc**	**Bus Type**	**SalCvLn TrmCtr**	**GpSales**	**CurRt**	**SolvRt**	**RpExFin**	**PayRec**	**G5num**	**G3num**	**Status**	**FcA rating**	**Z**
RO81	1	2	1	1	0.91	1	1.63	0.36	0	1	0%	0%	Bad	C	-0.27972